The Rising Value of Time and the Origin of Urban Gentrification

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Abstract

In recent decades, gentrification has transformed American central city neighborhoods. I estimate a spatial equilibrium model to show that the rising value of high-skilled workers’ time contributes to the gentrification of American central cities. I show that the increasing value of time raises the cost of commuting and exogenously increases the demand for central locations by high-skilled workers. While change in the value of time has a modest direct effect on gentrification of central cities, the effect is substantially magnified by endogenous amenity change driven by the changes in local skill mix.

Keywords: Gentrification, Value of time, Amenities, Central cities
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1 Introduction

Since the 1990s, American cities have seen a wave of urban revival during which the growth of income and home value in central city neighborhoods far outpaces that in the suburbs. This process, often called gentrification, is characterized by an influx of affluent, educated residents, as well as improving amenities and rising housing costs. This recent prosperity contrasts sharply with the long period of decline of central cities and the "flight" of affluent residents to the suburbs pre-1990s (Baum-Snow (2007), Boustan (2010)).

Previous papers have shown that the increasing valuation of central city amenities explains the rising demand for central cities by college-educated residents (Baum-Snow and Hartley (2020), Couture and Handbury (2020)). However, since local amenity change is likely an endogenous process (Guerrieri, Hartley, and Hurst (2013)), the improvement in central city amenities could be both a cause and a consequence of the inflow of high-skilled residents. To trace the causal origin of the central city revival after decades of persistent decline, one ought to identify the exogenous forces that push high-skilled urban "pioneers" back to the central cities despite the initially low level of amenities in these locations prior to gentrification and understand how these forces bring about the endogenous amenity change.

In this paper, I show that high-skilled workers' rising value of time is an exogenous force contributing to the gentrification of central city neighborhoods. The rising value of time among high-skilled workers makes central cities more attractive to them due to shorter commuting time to work. As high-skilled "pioneers" move into the central cities, amenity conditions endogenously improve, and rents increase due to increased demand for central city housing. The improved amenities make central cities increasingly attractive to high-skilled workers, despite rising rents. On the other hand, while facing the same rising rents, low-skilled workers demand these amenities much less than high-skilled workers do. As a result, low-skilled workers increasingly relocate to the suburbs while high-skilled workers increasingly sort into central city neighborhoods. I show that while the rising value of time among high-skilled workers has a modest direct effect on the gentrification of central cities, the resulting endogenous change in amenities substantially amplifies its direct effect.

I motivate my analysis by documenting that the time period of gentrification coincides with a period in which long working hours became more prevalent among high-wage earners. Evidence (Kuhn and Lozano (2008)) suggests that, before 1980, low-wage workers tended to work longer hours than high-wage workers. However, since mid-1980, this pattern has reversed itself. In recent years, high-wage workers have become much more likely to work long hours than their low-wage counterparts. Interestingly, since 1980, the growth of reported commute time is much slower among the workers in the top wage deciles than workers in lower wage deciles, suggesting that the spatial relocation of high-skilled workers into the central cities is likely related to their changing value of time and increasing desire for shorter commute time.

To evaluate how the value of time, commuting, and amenities affect neighborhood sorting, I present and estimate a spatial equilibrium model of neighborhood choice. In my model, I allow workers to choose which neighborhood to live in based on their value of time, the commute time to
their jobs, local amenities, and rents. My model allows the changing value of time to exogenously affect workers’ demand for shorter commuting time and allows local amenities and local rents to change endogenously as the local population mix changes. In the model, the mechanism of workers’ spatial sorting is governed by how much workers’ value of time, neighborhood amenities and rents each affect their demand for locations.

I estimate workers’ location demand using a novel empirical strategy. The first and the most important parameter of interest is how much the value of time affects the demand for shortening commute time. The size of this parameter determines how much high-skilled workers’ rising demand for central cities is directly attributable to their rising value of time. To identify this parameter, I exploit the fact that job locations in different occupations are distributed differently across space. If the rising value of time leads to workers shortening their commute time, I should see them moving closer to job locations specific to their occupations, all else equal. To think about the strategy more intuitively, consider financial workers and physicians in the New York MSA. Financial jobs are very concentrated in downtown Manhattan while clinics and hospitals are spread throughout the metropolitan area. Therefore, if financial workers and physicians both demand shorter commute time, they should move in different directions according to their respective job locations.

The other set of important parameters are workers’ preferences for local amenities. If high-skilled workers have a stronger demand for amenities like restaurants, gyms and other service amenities than low-skilled workers, the endogenously changing amenities could amplify the exogenous change induced by the the changing value of time. To identify these parameters, I use the idea that the locations of job sites that a worker does not work at may indirectly affect the worker’s migration choice by changing other workers’ migration choices and thus changing local amenities. In the previously used example of financial workers and physicians, downtown Manhattan has a high concentration of financial firms but has a smaller concentration of clinics and hospitals. The rising value of time of financial workers would induce an inflow of high-skilled financial workers and thus a rising level of amenities in downtown Manhattan. If I observe that physicians also increasingly migrate into downtown Manhattan, even though physicians do not typically work there, such patterns would reveal their preference for amenities.

To implement this empirical strategy, which exploits the variation in the changing value of time by occupation, I first measure workers’ value of time by estimating the "long-hour premium" for each detailed occupation, using repeated cross-sections from the Census data in 1990 and 2010. Using the differential changes in long-hour premiums in different occupations, I examine how much the value of time affects workers’ migration choices regarding commute time.

I measure the distance to job locations in the form of an "expected commute time," which is the average commute time weighted by the spatial distribution of jobs. To measure commute time, I construct a travel time matrix (by driving) generated by Google Distance Matrix API and National Household Travel Survey data. Such a travel time matrix provides me commute time between all neighborhoods within all MSAs in the U.S. I combine the travel time matrix with data on occupation-specific job locations to measure each residential neighborhood’s expected commute
Using the estimated model, I show that around 7% of the gentrification of central cities is driven by the direct effect of the shock to the value of time, holding amenities and rents constant at the initial levels. I further show that an additional 40% of the gentrification of central cities is driven by the indirect effect of endogenous amenity change. This means that the rising value of time is likely a contributing force behind gentrification, but its effect is greatly magnified by the effects of endogenous amenity improvement. The results also suggest that the changing value of time and the endogenous amenity change have significant but limited ability to explain the full magnitude of central city gentrification. Other factors are also likely to have played a crucial role.

Furthermore, I analyze the welfare consequence of gentrification through the lens of the model. I evaluate the effect of the change in the value of time, amenities, and rents on welfare inequality between high- and low-skilled workers. Relative to the rise in earnings inequality, the change in the value of time reduces welfare inequality moderately, as the rising value of time affects high-skilled workers disproportionately. However, the changing amenities and rents substantially widen the welfare inequality, entirely offsetting the effect of the changing value of time and leading to a net increase in welfare inequality.

Finally, I evaluate the effect of housing policies which lowers rent growth on gentrification and welfare inequality. I show that policies that lower rent growth likely lead to a rise in both high- and low-skilled populations in central cities, which would not have lowered the degree of gentrification as defined by the change in ratio of high- and low-skilled residents. On the other hand, lowering rent growth would likely have very a large impact on mitigating the rise in welfare inequality because low-skilled workers derive much larger welfare benefits from smaller rent growth relatively to high-skilled workers do. Low-skilled workers’ small migration response to rents, despite rents having a large welfare impact on them, is likely due to a high migration friction they face.

This paper is related to several strands of literature. First, the paper contributes to the literature that examines the mechanisms behind the striking phenomenon of urban gentrification in the United States. Edlund, Machado, and Sviatchi (2015) is the first paper that examines how high-skilled workers’ decreasing tolerance toward commuting induces them to move to the central cities, leading to gentrification. Inspired by their insights, my paper uses a spatial equilibrium model to demonstrate how the mechanisms play out through the rising value of time and endogenous amenity change, and I use a novel identification strategy to empirically pin down each of the mechanisms. Many alternative hypotheses have been examined by prior papers. Brueckner and Rosenthal (2009) examine the role of the aging cycle of housing stock in urban gentrification. Baum-Snow and Hartley (2020) and Couture and Handbury (2020) both find that amenity change and high-skilled workers’ valuation in amenities are important in explaining the recent changes in central cities. Behrens et al. (2021) find cultural and recreational "pioneer" businesses spurred gentrification of neighbor-

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1 I analyze welfare inequality rather than absolute welfare change because I do not have a good measurement of change in the absolute levels of amenities. I measure amenities by examining the skill mix of neighborhoods. Although the change in local skill mix over time can be a good approximation of the change in relative amenities, it is not a measurement for the change in absolute amenities. Therefore, spatial sorting can only inform me about the relative welfare changes across groups.
hoods around them. Couture et al. (2020) demonstrate that the income growth of the high-income workers and their non-homothetic preferences for luxury urban amenities are significant forces that gentrify the city centers. Ellen, Horn, and Reed (2019) examine the role of crime reduction, which is another important exogenous force that generates inflow of high-skilled residents.

This paper also contributes to how neighborhood amenities change in response to changes in resident mix, and how, conversely, these neighborhood amenities affect how different residents choose locations. Many papers highlight the role of amenities in the spatial economy (Brueckner, Thisse, and Zenou (1999), Glaeser, Kolko, and Saiz (2001), Bayer, Ferreira, and McMillan (2007), Guerrieri, Hurst, and Hartley (2011), Autor, Palmer, and Pathak (2014), Alboy and Lue (2015), Diamond (2016), Handbury (2019), Couture (2016), Couture and Handbury (2020), Davis et al. (2019), Autor, Palmer, and Pathak (2017), Hoelzlein (2019), Almagro and Dominguez-Iino (2021)). Glaeser, Kolko, and Saiz (2001) argue that cities are attractive to workers not only because they offer higher wages but also because their consumption amenities are greater. Another example is Guerrieri, Hurst, and Hartley (2013), who show that when cities experience positive labor demand shocks, incoming residents tend to demand housing near areas that were initially wealthy. In this paper, I identify workers’ preferences for amenities with a similar method used by Diamond (2016), which I apply at the neighborhood level.

Finally, this paper is closely linked to the literature on time-use. A number of papers have studied the effect of workers’ opportunity cost of time on intra-household or intra-personal time allocation between market work time and home production (Aguiar and Hurst (2007), Becker (1965), Benhabib, Rogerson, and Wright (1991), Goldin (2014), Nevo and Wong (2018)). My paper extends the analysis by investigating how the opportunity cost of time affects location choice and the housing market. My paper is particularly linked to and dependent on the work by Kuhn and Lozano (2008), who document the changing working-hour pattern among high- and low-income workers in the U.S.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 presents descriptive patterns from the data. Section 4 describes the spatial equilibrium model. Section 5 discusses the estimation methodology. Section 6 presents the results. Section 7 analyzes the determinants of gentrification. Section 8 analyzes the welfare results. Section 9 presents the conclusion.

## 2 Data

The main datasets I use are the 1990 U.S. Decennial Census data and the 2007-2011 American Community Survey (ACS). The 5% Integrated Public Use Microdata Series (IPUMS) dataset provides Census and ACS microdata at the individual level for a large variety of demographic and economic variables, such as income and occupation (Ruggles et al. (2017)). IPUMS also provides geocoded microdata down to the level of Public Use Microdata Areas (PUMA), which is useful for computing changing location demand for central cities across various demographic subgroups. I also use IPUMS’ national sample to estimate the value of time for each occupation.

Another data source for Census and ACS data is the National Historical Geographic Information System (NHGIS) (Manson et al. (2017)). The NHGIS provides summary files of the Decennial
Census at the census tract level for 1950, 1960, 1970, 1980, 1990, 2000, and also of the ACS for 2007-2011. This dataset enables me to analyze post-war trends of suburbanization and the subsequent gentrification at the census tract level. The NHGIS data also enable me to track workers’ occupation affiliations at the census tract level, which I use to construct location choice probability for each census tract by occupation.\footnote{Specifically, I use 1990 and 2007-2011 summary file data which provide the count of people in each occupation group at census tract level to impute a detailed occupation count at census tract level in combination with IPUMS microdata at PUMA level. The imputation procedure is detailed in Appendix section B1.}

I use the Zip Code Business Patterns (ZCBP) data, provided by the U.S. Census Bureau, to measure the spatial distribution of jobs for each occupation in 1994 and 2010 (U.S. Census Bureau (2017)).\footnote{The employment location imputation procedure is described in Appendix section B2.} The ZCBP is a comprehensive dataset at the Zip Code Tabulation Area (ZCTA) level developed from the Census’s Business Register. I also use the ZCBP data for locations of amenities such as restaurants. In addition, I use the Uniform Crime Report for data on local violent and property crimes (U.S. Department of Justice (2017)).

I measure commute time between each residential location and each potential work location within any given MSA. To do so, first, I use the Google Distance Matrix API to compute travel time\footnote{Travel time is computed with the traffic feature turned off.} and travel distance from every census tract to every ZCTA (Zip code) centroid within each MSA. Then, I adjust for historical traffic conditions using an auxiliary dataset, the 1995 National Household Travel Survey (NHTS).\footnote{I do so by estimating a travel-speed model based on route distances and location characteristics of each trip’s origin/destination, with trip samples that take place at rush hour during weekdays in 1995 (U.S. Department of Transportation (2009), Couture (2016)). A detailed description of how I generate the travel matrix is included in the Appendices B3 and B4.}

\section{Descriptive patterns}

To motivate the linkage between gentrification, the rising value of time, and the amenity change, I document a few stylized facts that describe the gentrification patterns and time-use patterns observed over the past decades.

\subsection{Gentrification}

First, the growth of household income and home value in central city neighborhoods far outpaces that in suburban neighborhoods in the past three decades, which reverses decades of declining trends in central city neighborhoods. As shown in Figure 1, the ratio between average household income in central city neighborhoods (within 5 miles of the geographic pin of downtown by Google Map for the 25 most populous MSAs\footnote{I use the downtown definition provided by Holian and Kahn (2015). The locations of city centers are based on the pins returned from searching for the cities in Google Earth.}) and suburban neighborhoods drops to its lowest value in 1980.\footnote{Figure A2 in the appendix shows the evolution of income ratio by MSA population ranking. A breakdown of income ratios by MSA ranking shows that much of the gentrification phenomenon occurred in large metropolitan areas.} The home value ratio between the central city and suburban...
neighborhoods drops to its lowest value in 1970 and remains relatively low, until both income ratio and home value ratio shoot up after 1990. In Figure 2, I plot the census tract level change in log skill ratio between 1990 and 2010 by distance to downtown (skill ratio is defined as the ratio between the number of the residents of high-skilled occupations and the residents of low-skilled occupations. High-skilled occupations are defined as occupations with ≥ 40% of college graduates in the 1990 Census). The plot shows a dramatic increase in the presence of high-skilled residents near downtown locations. The rising skill composition near downtown locations was significant in both decadal periods of 1990-2000 and 2000-2010.

However, while high-skilled residents are increasingly living in central city neighborhoods, the locations of high-skilled jobs have not been centralizing. Figure 3a is a binned scatterplot between the changes in shares of residents living in central city neighborhoods across MSAs in 1990 and in 2010. The plot shows that residential concentration in central cities rose significantly for high-skilled occupations, while the residential concentration generally declined for low-skilled occupations. However, the binned scatterplot in Figure 3b shows that the concentration of job locations is slowly decreasing over time, and high-skilled jobs do not exhibit particularly different sorting patterns than do low-skilled jobs. These observations show that the increasing residential demand for central city neighborhoods is unlikely to be driven by concurrent sorting of jobs.

The growth of high-skilled residents in central cities tends to be concentrated in previously low-income neighborhoods. Figure 4 shows the percentage distributions of the increase of high-skilled residents in central city neighborhoods between 1990 and 2010 by neighborhood income ranking. The numerators are the increases in the number of high-skilled residents in central city neighborhoods of each income quintile (ranked within MSAs as a whole), and the denominator is the total increase in the number of high-skilled residents in central city neighborhoods. Neighborhood income rankings used in Figure 4a is based on 1980 income levels. An overwhelming fraction of the growth of high-skilled residents in central cities occurred in neighborhoods previously low-income in 1980. This suggests that gentrification in central cities is unlikely driven initially by the previously existing amenities associated with high-income residents. In contrast, Figure 4b, which plots the percentage distribution of the increase in the number of high-skilled residents by neighborhood quintile in 2000, shows that many of the gentrifying neighborhoods have become high-income by 2000. By then, it is likely that neighborhood amenities may have endogenously improved.

The terms "gentrification" or "urban revival" may give the impression that central neighborhoods are now seeing faster overall population growth than the suburbs. However, while central neighborhoods may be gaining in terms of absolute population, they have not gained in terms of the share of overall MSA population, since population growth in the suburbs continues to outpace that in central cities. U.S. cities overall were still suburbanizing as recently as from 2000 to 2010, but at a much slower pace. Figure A8 in the appendix shows the share of central neighborhoods’ population as a percentage of total metropolitan population in the 25 most populous MSAs. The revived demand for central neighborhoods comes primarily from high-income workers, not all workers.

Figure A9 in the appendix shows the degree of job and residential concentration in central cities by occupation. Job locations by industry and occupation can be highly clustered and sticky to locations due to agglomeration and coagglomeration effects, as demonstrated by Ellison and Glaeser (1997), Rosenthal and Strange (2004), and Ellison, Glaeser and Kerr (2010).

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Such improved amenities could potentially further increase the desirability of these neighborhoods for high-skilled residents.

Indeed, I find that an increased presence of high-skilled workers tends to be accompanied by an improvement in local amenities. Diamond (2016) and Couture and Handbury (2020) have documented similar patterns. In Table 1 columns (1)- (4), I show the relationship between log per-capita counts of four types of consumption establishments (restaurants, grocery stores, gyms, and personal services) and the changes in log skill ratios at the census tract level. Results show that the census tracts that see stronger growth in skill ratio tend to also experience stronger growth in the abundance of amenities. In columns (5) and (6), I show the relationship between changes in log crime rates and changes in log skill ratios at the municipal level and find that stronger growth in skill ratios is associated with declining crime rates.

3.2 The prevalence of working long hours

Interestingly, the change in central cities around 1990-2010 is accompanied by the reversal of work-hour patterns in both the high-wage population and the low-wage population. Before 1990, high-wage workers generally were less likely to work long hours than low-wage workers (Kuhn and Lozano (2008)). However, since 1980, high-wage workers have become increasingly likely to work long hours, while working long hours have become less common for low-wage workers. Meanwhile, high-wage workers experienced much slower growth in commute time than lower-wage workers. Figure 5a shows the relation between the wage decile and the change in the percentage of workers working at least 50 hours a week in 1980 and 2010 using Census data.1011

The increasing prevalence of working long hours among high-skilled workers since the 1980s, coupled with the fact that job locations are highly concentrated in central city locations, suggests that the rising cost of time among high-skilled workers could have driven up their demand for housing in central city neighborhoods for the convenient commuting time.12 Consistent with this conjecture, I show in Figure 5b that while commute time in all wage groups has increased between 1980 and

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10I restrict my sample to workers who report working no less than 30 hours (to avoid overestimating wage due to measurement error in reported work hours). In 1980 and 2010 respectively, I put each worker’s wage into wage decile bins, and for each bin, I compute the percentage of workers who report working more than 50 hours a week. In calculating the percentage of long hour workers, I restrict the sample to males, aged 25-65, who work at least 30 hours per week. I exclude females from this calculation because I want to avoid the increase in female labor participation, which could confound the statistics.

11This pattern is not likely driven by spatial sorting into the central cities. Figure A17 in the appendix shows that by splitting the sample into workers living in central cities and the suburbs, similar patterns arise. In addition, if I split the sample not by income decile, but by college attainment, I get the similar pattern (Figure A18a).

12In addition to using Census/ACS data, I use the CPS to show this dramatic reversal in the context of a long-run trend (Flood et al. (2018)). For each year, I compute the probability of working long hours by using a three-year moving sample. I restrict the sample to male workers aged 25-65 working at least 30 hours a week (full-time workers). In Figure A4 in the appendix, I plot the probability of working long hours for workers at the top and bottom wage deciles, respectively. Consistent with the Census data, low-wage workers were more likely to work long hours prior to 1980. Since then, low-wage workers are increasingly less likely to work long hours. In contrast, high-wage workers’ probability of working long hours remains stable before the early part of the 1980s. But between the mid-1980 and late 1990, high-wage workers’ probability of working long hours increased dramatically.
2010, the growth in higher-wage groups is considerably smaller. This suggests that a substantial portion of higher-wage workers have re-optimized their locations in favor of shorter commute time.\(^{13}\)

### 3.3 Reduced-form relations between long hours and central city location choice

To validate the conjecture empirically, I show some reduced-form evidence that workers who increasingly work long hours are more likely to move into the central cities. I cut worker samples into detailed occupations and examine whether workers in occupations with rising incidence of working long hours between 1990 and 2010 are increasingly likely to live in central cities.

Table 2 columns 1-3 show the results of the occupation-MSA level first-difference regressions. I regress the change in the log share of residents living in central cities on change in log percentage of working long hours. The results show that workers in increasingly long-hour occupations are increasingly likely to live in central cities. In columns 4-6, I use the change in log commute time (observed directly in the Census/ACS data) by occupation as the outcome variable. The results show the workers in increasingly long-hour occupations tend to report relatively shorter commuting time.

While these results suggest that increasing long-hour work may have contributed to spatial sorting, it may be difficult to interpret the coefficients as strictly causal. First, workers increasingly working long hours are disproportionately high-skilled. If high-skilled workers have a time-varying taste for central city amenities, it could lead to bias. Second, if amenities are endogenous to the inflow of high-skilled residents, the initial sorting of the high-skilled could endogenously lead to further sorting of high-skilled residents. It is difficult to disentangle that with these simple regressions above.

I next perform an analysis using a spatial equilibrium model at the census tract level to separately identify the effect of the rising value of time, endogenous amenity changes, and rent changes on location choice and unpack the mechanism of gentrification.

### 4 Spatial equilibrium model of residential choice

I model workers’ neighborhood choice as a function of their value of time, commute time to and from where they work, amenity levels, and rents, where amenities and rents can endogenously adjust in equilibrium. Instead of modeling locations as binary, such as central cities or suburbs, I treat each census tract as a distinct location.

\(^{13}\)Interestingly, in the two decades between 1980 and 2000, the negative relation between growth of commute time and wage decile is very strong, while the relation is weakly positive between 2000 and 2010. This further suggests that the incentive to reduce commute time is likely an important initial reason why central cities became desirable among the skilled workers. Once the amenities started to improve and the feedback mechanism kicks in, the role of improving amenities in the central cities becomes gradually more important in attracting high-skilled workers than shorter commute time. In fact, the self-sustaining endogenous improvement in amenities in the central cities would lead to the rising prevalence of reverse-commute, which explains the slight positive relationship between growth in commute time and wage decile between 2000 and 2010. Despite the conjecture, the formal analysis in this paper does not deal with the precise timing of the mechanism. I do provide supporting evidence in Appendix C4 to shed some light on the timing.
4.1 Worker’s problem

Given a worker’s occupation $k$ and city $m$ where she lives and works, a worker who chooses to live in neighborhood $j$ and works in neighborhood $n$ in year $t$ enjoys utility:

$$U(C, H, A_{jmt}, c_{jnmt}) = C^\theta H^{1-\theta} \tilde{A}_{jmt} \exp(-\tilde{\omega}_t c_{jnmt}) \exp(\sigma_k \varepsilon_{i,jmt})$$  
(1)

subject to budget constraint

$$C + R_{jmt} H = \exp(y_{0kt} + v_{kt} (T - c_{jnmt})).$$

$C$ is the consumption of numeraire goods; $H$ is the consumption of housing services; $A_{jmt}$ is the amenity level for neighborhood $j$ at time $t$; $\tilde{A}_{jmt}$ is the taste parameter for local amenities, which may differ by worker type $k$; $c_{jnmt}$ is the weekly commute time between residential location $j$ and work location $n$. $\tilde{\omega}_t$ is a time-variant aversion parameter for commute time. $\varepsilon_{i,jmt}$ is the idiosyncratic preference for individual $i$, distributed as Type I Extreme Value, and $\sigma_k$ is its standard deviation. I normalize the price of consumption good $C$ to be 1, and I let $R_{jmt}$ be the rental price for housing services in $j$ at time $t$.

4.1.1 Long-hour premium

A worker’s log earnings consist of two components: weekly earnings that she receives if she were to supply 40 hours of work $y_{0kt}$, and the extra earnings she receives from additional hours supplied beyond 40 hours $v_{kt} (T - c_{jnmt})$. $v_{kt}$ measures the log weekly earnings from each extra hour of work supplied in a week, which I call the "long-hour premium" (Kuhn and Lozano (2008)). $T$ is the worker’s total possible hours supplied beyond 40 hours per week. For a worker facing a large $v_{kt}$, she would be facing a high penalty of living far from work. The size of the long-hour premium is used to approximate workers’ value of time in this model.

This method differs from the traditional way of measuring the value of time using hourly earnings.

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14I use MSAs to represent cities. Given the choice of an MSA, a worker can choose which neighborhood to live in within that MSA. The reason I use MSA as a city unit for the analysis instead of commuting zones (CZs) is that CZs are constructed at a lower geographic level. For example, Jersey City, NJ belongs to the Newark CZ, which is different from the New York CZ, even though commute time from Jersey City to downtown New York is around 10 minutes. The New York MSA, on the other hand, covers both Newark and New York CZs. In this model, I would want workers who work in downtown New York to have the choice to live in Jersey City, NJ. Therefore, in the context of this analysis, MSA is a more natural choice.

15I allow the log-transformed amenity level to be decomposed into a uni-dimensional observable amenity level and an unobservable component: $\log(A_{jmt}) = a_{jmt} + \zeta_{jmt}$.

16Long commute could dip into people’s work hours, which lowers earnings. A possible hypothesis is that long commute time may not necessarily dip into a worker’s work hours directly, but may instead eat into the worker’s leisure hours. The predicted effect of value of time on locational sorting is robust to this assumption. Under the assumption that work hours and leisure hours can be easily reallocated within a worker, the marginal value of leisure hours would equal the marginal value of work hours. In that case, a rise in the value of work hours (long-hour premium) would imply that the value of leisure hours rises at the same rate, which would generate the same effect on location choice, even if the worker decides to keep his/her work hours unchanged. In Appendix A2, I derive another specification in which leisure is another margin of choice but is separable from consumption, the resulting empirical equation is equivalent with the one without leisure choice.
or wages. Using wage as the value of time may work for workers who are paid by the hour. However, for non-wage workers, who are paid with fixed salaries, commissions, or more complex forms of compensation schedules, their pay may not be a linear function of their hours worked. Consider a teacher who works in a K-12 school and receives a fixed salary for 40 hours of weekly teaching obligations. Working more hours than 40 hours (e.g., spending extra time helping students with homework) would not necessarily increase earnings. In contrast, for a financial manager, receiving a bonus and or getting a promotion may depend crucially on the hours and effort devoted to the job. As a result, the financial manager’s marginal incentive of hours supply may even exceed the average hourly earning and may be compensated disproportionately if she works longer hours (Goldin (2014)).

The long-hour premium measured in the unit of log earnings captures the percentage return of working extra hours. This measure is designed not to be sensitive to the level differences in earnings across occupations and only captures the differential incentives to supply hours at the intensive margin.

4.1.2 Location demand

Given the utility set up, each worker solves a two-step utility-maximization problem.

In the first step, the worker chooses the optimal level of consumption $C$ and housing services $H$, given her occupation and the locations she lives and works at. The maximization problem renders an indirect utility for each location and occupation.

After normalizing the indirect utility function by $\sigma_k$, I can write down the indirect utility of workers $i$ live in $j$, working in $n$ as follows:\footnote{Derivation of the indirect utility is detailed in Appendix A1. The structural forms of the linear coefficients in the indirect utility can be found in the appendix as well.}

$$V_{i,jnmt} = \delta_{mkt} - \mu_k v_{kt} c_{jnmt} - \omega_k t_{c_jnmt} - \beta_k r_{jnmt} + \gamma_k a_{jnmt} + \gamma_k \zeta_{jnmt} + \varepsilon_{i,jnmt}. $$

$$a_{jnmt} = \ln (A_{jnmt}) \text{ and } r_{jnmt} = \ln (R_{jnmt}).$$

In the second step, worker $i$ chooses residential neighborhood $j$ within MSA $m$ to maximize indirect utility. Since $\varepsilon_{i,jnmt}$ is distributed as Type I Extreme Value, the probability that worker $i$ would choose neighborhood $j$ is given by a multinomial logit function (McFadden (1973), Berry (1994)).

After derivation, written in detail in Appendix A3, I write the log location choice probability as
a linear function of various location preference components:

$$\log(s_{jmk}) = \delta_{mk} + \log\left(\sum_{n'\in J_m} \pi_{n'mk} \exp\left(-\left(\omega_{kt} + \mu_k v_{kt}\right) \cdot c_{jn'mt}\right)\right)$$

(2)

$$- \beta_k r_{jmt} + \gamma_k a_{jmt} + \gamma_k u_{jmt}$$

valuation of proximity to employment
valuation of rent
valuation of amenities
valuation of unobserved amenities

$$s_{jmk}$$ is the probability of choosing neighborhood $$j$$ by workers in occupation $$k$$ living in MSA $$m$$ in year $$t$$. Workers value the proximity to jobs, neighborhood amenities, and lower rents. $$\pi_{n'mk}$$ is the fraction of jobs within MSA $$m$$ located in neighborhood $$n'$$. The specification allows that workers gravitate toward living close to locations with a large number of jobs in their respective occupations.

The specification is nonlinear with respect to the value of time $$v_{kt}$$. To illustrate the marginal effect of the value of time $$v_{kt}$$ on demand for neighborhoods more clearly, I take the derivative of the log $$(s_{jmk})$$ with respect to the value of time: 18

$$\frac{\partial \log(s_{jmk})}{\partial v_{kt}} = \tilde{\delta}_{mk}' - \mu_k \tilde{E}_t(c_{jmk})$$

(3)

$$\tilde{E}_t(c_{jmk})$$ is the expected commute time for workers in occupation $$k$$ living in $$j$$. This is the average commute time weighted by the spatial distribution of jobs of occupation $$k$$. 19 The specification shows that increasing the value of time would lead to a rising demand for shorter commute time. $$\mu_k$$ governs how much the value of time affects workers’ sensitivity to commute time when making location choices.

4.1.3 Endogenous amenity supply

I assume that the level of amenities in each neighborhood can respond to the local ratio of local high-skilled and low-skilled residents, similar to the assumption made by Diamond (2016). 20 Under this assumption, a rising share of high-skilled residents in a neighborhood would potentially lead to

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18 The fixed effect $$\delta_{mk}$$ is city $$m$$- and occupation $$k$$-specific, but not neighborhood $$j$$-specific. See Appendix A3 for detailed explanation. Therefore, even though the fixed effect is a function of the value of time $$v_{kt}$$, the derivative of the term would be city $$m$$- and occupation $$k$$-specific, can be accounted for as $$\delta_{mk}'$$.

19 $$\tilde{E}_t(c_{jmk}) = \sum_{n \in J_m} \tilde{\pi}_{jnmt} c_{jnmt}$$, where $$\tilde{\pi}_{jnmt}$$ is an adjusted probability measure as: $$\tilde{\pi}_{jnmt} = \frac{\pi_{nmt} \exp\left(-\left(\omega_{kt} + \mu_k v_{kt}\right) c_{jnmt}\right)}{\sum_{n' \in J_m} \pi_{n'mt} \exp\left(-\left(\omega_{kt} + \mu_k v_{kt}\right) c_{jnmt}\right)}$$. The adjusted $$\tilde{\pi}_{jnmt}$$ is the probability of working in neighborhood $$n$$ by worker of occupation $$k$$ who lives in neighborhood $$j$$. The adjustment takes into account the fact that workers are less likely to work at locations too far away from home.

20 Some amenities are in the form of natural amenities such as parks and natural sceneries (Lee and Lin (2017)); some are in the form of public goods (e.g., crime and law enforcement), and others are in the form of consumption venues such as restaurants, retail stores, fitness facilities, etc. (Couture and Handbury (2020)).
the entries of suppliers of local goods and services and better funding for local public goods, such as effective local law enforcement.  

$$a_{jmt} = \eta \ln \left( \frac{N^H_{jmt}}{N^L_{jmt}} \right) + \tilde{\theta}_t X_{jmt} + \delta_{jm} + \delta_{mt} + \xi^a_{jmt}. \quad (4)$$

$N^H_{jmt}$ and $N^L_{jmt}$ are the counts of high- and low-skilled workers living in neighborhood $j$. $\eta$ represents the amenity supply elasticity with respect to the local skill ratio. $X_{jmt}$ represents other observable neighborhood characteristics that workers may value, and I allow them to contribute to the amenity level at rate $\tilde{\theta}_t$. $\delta_{jm}$ represents census tract fixed effects, and $\delta_{mt}$ represents MSA/time fixed effects. $\xi^a_{jmt}$ represents the unobservable component of amenity supply not driven by the local skill ratio.

Since a key driver of amenity supply is the local skill ratio, I endogenize amenity levels into workers’ location demand by directly modeling location demand as an iso-elastic function of local skill ratios, governed by a reduced-form migration elasticity $\gamma_k$. Ideally, I would like to model neighborhood amenities directly. It is, however, difficult to aggregate multiple dimensions of amenity variables into a single amenity.  

Since the change in local skill ratio captures the content of amenity change driven by the changing local population mix, I use local skill ratio to capture the endogenous amenity mechanism in the model and create measurements of crime and consumption amenities later in the paper and provide separate evidence that these amenity levels do respond to shocks to local skill ratios.

By plugging the amenity supply function into location demand, I get the following equation:

$$\log (s_{jmkt}) = \tilde{\delta}_{mkt} + \log \left( \sum_{n' \in J_m} \pi_{n'mkt} \exp \left( - (\omega_{kt} + \mu_{kt} v_{kt}) \cdot c_{jn'mt} \right) \right) - \beta_k r_{jmt} \quad (5)$$

$$+ \gamma_k \log \left( \frac{N^H_{jmt}}{N^L_{jmt}} \right) + \theta_{kt} X_{jmt} + \gamma_k \xi^a_{jmt} + \gamma_k \xi^*_{jmt}.$$  

The reduced-form migration elasticity $\gamma_k$ is a combination of demand-side elasticity and supply-side elasticity, namely $\gamma_k \eta_k$; this is a sufficient statistic that can pin down the mechanism of the endogenous amenity change. $\theta_{kt} X_{jmt}$ is the component of amenities that is observable and exogenous. $\gamma_k \xi^a_{jmt}$ is the component of amenities that does not covary with local residential composition.

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21The assumption is also consistent with what Guerrieri, Hurst, and Hartley (2013) find: at the neighborhood level, people like to live close to a wealthy neighborhood, and therefore it is possible that local residential composition may directly influence people’s location preference.  

22This may include amenities of a cultural and/or historical nature, which would affect neighborhood amenities regardless of the inflow and outflow of local residents.  

23Alternatively, I could model each type of amenity in the model. Using that approach, I would face an identification challenge. To separately identify preference parameters for different types of amenities (law enforcement, consumption venues, and public infrastructure), I need identifying variations for each one of these amenities. If I create an amenity index that measures overall local amenity level $a_{jmt}$, I would still have to take a stance on how different measures of amenities ought to be aggregated, and it is difficult to favor one method over another. A recent paper by Almagro and Dominguez-Iino (2021) provides a novel analysis of neighborhood amenities with multiple dimensions of amenity types.  

24The parameter $\theta_{kt}$ is a reduced-form combination of demand-side and supply-side parameters. $\theta_{kt} = \gamma_k \tilde{\theta}_t$. 

12
Since $\gamma_k\xi_j^m$ and $\gamma_k\zeta_j^m$ are both unobservable, I denote the sum of the two terms as $\xi_j^{mkt}$.

### 4.2 Housing supply

I assume that log rent is a reduced-form function of local demand for housing and its interaction with the existing housing stock density $\text{den}_j$. The intuition is that the elasticity of housing supply at the micro-geographic level depends on the neighborhood’s availability of developable land. If a neighborhood already has a high density of existing structures, the the marginal cost of constructing new housing would be higher and therefore new housing units would be supplied more inelastically. A recent paper by Baum-Snow and Han (2020) shows that existing development is a substantial driving force behind housing supply elasticity at the micro-geographic level.\(^{25}\)

I measure the local housing demand by the aggregate income of residents in the neighborhood, which is $\sum_k \tilde{Y}_{mkt}N_{jmkt}$, where $\tilde{Y}_{mkt}$ is the income of workers of occupation $k$ in city $m$ at time $t$. Additionally, there is a national housing demand shock, captured by $\iota_t$. The following is the inverse housing supply equation:

$$r_{jmt} = \pi \text{den}_{jm} \log \left( \frac{D_{jmt}}{\text{housing demand}} \right) + \delta_{mt}^r + \xi_{jmt}^r$$

$$D_{jmt} = \exp (\iota_t) \sum_k \tilde{Y}_{mkt}N_{jmkt}$$

$\pi \text{den}_{jm}$ represents the inverse elasticity of housing supply at the local level. $\xi_{jmt}^r$ represents unobserved housing supply components, which could come from the variation in construction costs specific to neighborhood $j$ but unrelated to initial housing stock density. $\delta_{mt}^r$ is the MSA-time fixed effect.

### 4.3 Equilibrium

Equilibrium is defined as the residential location demand $s_{jmkt}$, as well as rent $r_{jmt}$, such that:

1. **Amenity market clears in each census tract:** The amenities market clears if local skill ratios (amenity supply) lead to location choices such that the resulting local skill ratios (amenity demand) are consistent;

2. **Housing market clears in each census tract.**

I cannot solve the system of equations analytically. Even so, the equilibrium framework is useful when I estimate the model parameters. In the estimation section, instrumental variables will be constructed using the framework from the model.

\(^{25}\)The more commonly used housing supply elasticities/costs of construction measured by Saiz (2010) can only be used at aggregate levels, such as the MSA level.
5 Estimation

5.1 The long-hour premium

The first model component I estimate is the change in the long-hour premium for each occupation over time. To estimate the change in the long-hour premium, I take the labor earnings function in the model to the microdata from the Decennial Census and the ACS and estimate the long-hour premiums for each occupation in 1990 and 2010. The equation to be estimated is the following:

\[
\log Y_{ikt} = y_{0kt} + v_{kt} \text{hour}_{ikt} + \delta_{\text{demo},it} + u_{ikt}.
\]  

(7)

I denote the variable \( \text{hour} \) as weekly work hours in excess of 40. \( y_{0kt} \) is the log weekly earnings the worker would earn if she worked 40 hours/week. \( v_{kt} \) is the long-hour premium to be estimated. \( \delta_{\text{demo},it} \) is the vector of demographic fixed effects. \( u_{ikt} \) is the error term.

I estimate the long-hour premium \( v_{kt} \) using cross-sectional data on log earnings and hours within each occupation, controlling for individual workers’ characteristics.\(^{26}\) Since hours worked is a labor supply choice variable, estimates of the long-hour premium may be driven by a selection effect related to unobserved worker ability. I describe in detail how I address endogeneity concerns in Appendix section D1. For the estimates of the long-hour premiums for all occupations, see Table A10 in the appendix.

5.1.1 Reduced-form relations between long-hour premium, long-hour work, central city location choice, and job locations

Once I estimate the long-hour premiums \( v_{kt} \) for all occupations in 1990 and 2010, I conduct a validation test by regressing the change in the log probability of working long hours on the change in the long-hour premium. The results in Table 3 show that workers in occupations with rising long-hour premiums indeed are increasingly likely to work long hours. Table 3 also shows that workers in occupations with rising long-hour premiums are increasingly likely to live in the central cities. The change in log reported commute time is also negatively correlated with long-hour premium.\(^{27}\)

5.2 Location demand

Next, I proceed to discuss the identification of the key model parameters. The key parameters to identify in the location demand equation are \( \mu_k, \gamma_k, \beta_k \). I allow these parameters to differ by skill:

\(^{26}\)To establish the intuition for how the cross-sectional relationship between log earnings and hours worked can pin down the long-hour premium, I show in Figure A10 the plots between residual log weekly earnings and hours worked for four occupations. For financial workers and lawyers, the slopes rise dramatically from 1990 to 2010. In contrast, for office secretaries and teachers, the slopes of the plots remain largely unchanged, despite increases in average hourly earnings over time.

\(^{27}\)In Figure A11 in the appendix, I further document that while jobs generally are spatially concentrated in central cities, high-skilled jobs are disproportionately concentrated in central cities. In particular, the high-skilled jobs with a large increase in the long-hour premium are even more disproportionately concentrated in central cities. The heavy initial presence of work locations for high-skilled workers with rising long-hour premium in central cities is consistent with high-skilled workers disproportionately choosing to move into the central city neighborhoods.
\[ \mu_z, \gamma_z, \beta_z \] such that \( z \in \{ H, L \}.^{28} \)

Note that in specification (5), \( \mu_z \) enters the equation nonlinearly. To simplify the estimation equation, I use a Taylor approximation so that the location demand is a linear function of \( \mu_z \). The following is the linearized location demand:\(^{29}\)

\[
\log (s_{jmkt}) = \delta_{jm} + \tilde{\delta}_{mkt} - (\phi + \omega z t) \tilde{E}_t (c_{jm}) - \mu_z v_{kt} \tilde{E}_t (c_{jm}) - \beta_z r_{jmt} + \gamma_z \log \left( \frac{N_{jm}^H}{N_{jm}^L} \right) + \theta_k t X_{jm} + \xi_{jmkt} \tag{8}
\]

\( \tilde{E}_t (c_{jm}) \) is the expected commute time weighted by job distribution of time \( t \).\(^{30}\) \( \mu_z \) is the migration elasticity with respect to the expected cost of commute measured in the unit of log income. \( \delta_{mkt} \) is the city-occupation-time fixed effects, and \( \delta_{jm} \) is the neighborhood-occupation fixed effects, which account for the constant terms from the Taylor approximation.

After taking the first difference, we get the change in location demand:

\[
\Delta \log (s_{jmkt}) = \Delta \tilde{\delta}_{mkt} - \Delta \omega z t \tilde{E}_{t-1} (c_{jm}) - \mu_z \Delta v_{kt} \tilde{E}_{t-1} (c_{jm}) - \beta_z \Delta r_{jmt} + \gamma_z \Delta \log \left( \frac{N_{jm}^H}{N_{jm}^L} \right) + \varphi_{kt} \Delta \tilde{E}_t (c_{jm}) + \Delta \theta_k t X_{jm} + \Delta \xi_{jmkt}, \tag{9}
\]

where \( \varphi_{kt} = - (\phi + \omega z t + \mu_z v_{kt}) \). I do not impose any restriction on the structure of \( \varphi_{kt} \) and allow it to freely vary by occupation. I let \( X_{jm} \) be time-invariant, thus \( X_{jm} \), and let it be the expected commute time weighted by initial locations of all jobs, excluding occupations similar to workers’ own occupation, as a measure of location centrality. I allow each occupation to have an arbitrarily changing preference \( \Delta \theta_k t \) for such location centrality measure, so that spatial sorting due to changing preference for central cities is accounted for.

### 5.2.1 Identification of parameters

With this setup, I discuss the identification of the three sets of parameters: \( \mu_z, \gamma_z, \beta_z \) in detail.

**The identification of \( \mu_z \):** To identify \( \mu_z \), I exploit the fact that job locations are spatially distributed differently for different occupations. If location \( j \) is near a large concentration of jobs in occupation \( k \), \( \tilde{E}_{t-1} (c_{jm}) \) would be small, because short commute times would receive large weights. Therefore, if the rising value of time makes workers move closer to work, I should see them move toward their occupation-specific job locations, which are locations with shorter \( \tilde{E}_{t-1} (c_{jm}) \).

By observing the differential migration patterns by occupation and observing how much workers in occupations with increasing value of time migrate to locations with smaller \( \tilde{E}_{t-1} (c_{jm}) \), I can

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\(^{28}\)The implicit assumption is that \( \sigma \) differs by skill.

\(^{29}\)Since I only have a static travel time matrix, the commute time is set to be time-invariant. Derivation of the linear approximation is included in Appendix D4.

\(^{30}\)As a result of the Taylor approximation, \( \tilde{E}_t (c_{jm}) \) is evaluated with a transformed probability measure, \( \tilde{\pi}_{jm,k,t} = \frac{\pi_{jm,k,t} \exp(-\phi c_{jm})}{\sum_{m' \in J_{jm}} \pi_{j,m',k,t} \exp(-\phi c_{jm'})} \), where I calibrate \( \phi \) such that the mean commute time matches the value reported in the 1990 Census data. \( \pi_{jm,k,t} \) is the unconditional probability measure of job distribution of occupation \( k \) at time \( t \). \( \phi \) is calibrated to be 0.3425.
identify $\mu_z$.

My identifying assumption is that the change in the taste for unobserved neighborhood amenities $\Delta \xi_{jmkt}$ is uncorrelated with initial job locations $\tilde{E}_{t-1} (c_{jmk})$, namely $E \left( \Delta \xi_{jmkt} \tilde{E}_{t-1} (c_{jmk}) \right) = 0$. A violation of the identifying assumption would occur if the change in taste for unobserved amenities is correlated with initial job locations. To provide intuition, I use examples of financial workers and doctors. Assume financial workers increasingly prefer some unobserved amenities at location A to those at B, while doctors increasingly prefer some unobserved amenities at location B to those at A. If location A has a high initial concentration of financial jobs and location B has a high initial concentration of hospitals, the identifying assumption would be violated. In this case, the rising demand for locations closer to work could be driven by the increasing desire for unobserved amenities, rather than a changing demand to be close to work.

One practical concern for identification in my empirical setting is that locations with small $\tilde{E}_{t-1} (c_{jmk})$ tend to be in central cities, which may have unobserved amenity features for which workers have time-varying preferences, such as cultural, architectural, and artistic amenities typically found in historic downtowns. This could potentially lead to $E \left( \Delta \xi_{jmkt} \tilde{E}_{t-1} (c_{jmk}) \right) \neq 0$, a violation of the identifying assumption. As mentioned previously in the setup, to ensure identification, I include an occupation-invariant centrality measure $X_{jm}$ in the equation and allow workers to have differentially (by occupation) changing taste for such a measure. By doing so, the residual $\Delta \xi_{jmkt}$ is less likely to be systematically correlated with $\tilde{E}_{t-1} (c_{jmk})$.

The identification of $\gamma_z$: $\gamma_z$ is the migration elasticity with respect to local skill ratio

$$\log \left( \frac{N_{H,jmkt}}{N_{L,jmkt}} \right).$$

Naively regressing the change in location demand on the change in skill ratio would clearly produce severely biased estimates because the observed change in local skill ratios $\Delta \log \left( \frac{N_{H,jmkt}}{N_{L,jmkt}} \right)$ is mechanically driven by the changes in location demand, which is the left-hand side variable. To identify $\gamma_z$, I need to construct instrumental variables that shift the change in local skill ratio but are uncorrelated with $\Delta \xi_{jmkt}$.

To construct the instrumental variables, I exploit the idea that locations of jobs that are unrelated to a worker’s occupation may indirectly affect that worker’s migration choice through changing other workers’ migration choices and thereby changing the local skill ratio. Based on this idea, I compute the predicted log change in census tract populations of high- and low-skilled workers, driven purely by the differential changes in the value of time and job locations by occupation, as the instrumental variables for the change in local skill ratio. The following is the predicted population in census tract $j$ of occupation $k$:

$$\hat{N}_{jmkt} = N_{mk,t-1} \cdot \frac{\exp \left( \log (s_{jmkt,t-1}) - \hat{\mu} \Delta \hat{v}_{kt} \tilde{E}_{t-1} (c_{jmk}) \right)}{\sum_{j' \in J_m} \exp \left( \log (s'_{jm't-1}) - \hat{\mu} \Delta \hat{v}_{kt} \tilde{E}_{t-1} (c'_{j'mk}) \right)},$$

where $\hat{\mu}$ is the preliminary parameter estimate from estimating the unconditional location demand equation without including amenities or rent.$^{31}$ The predicted log population changes of high- and

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$^{31}$I set the value of $\hat{\mu}$ to be 8.94. In fact, the size of $\hat{\mu}$ does not matter in the size of estimates for the parameters of interest, even though it does affect the first-stage of the estimates. This is the case because $\hat{\mu}$ provides a scale for
low-skilled workers, respectively, are then $\Delta \log \hat{N}_{jmt,-k}^l = \log \left( \sum_{k' \in K_l} \hat{N}_{jmkt} \right) - \log \left( \sum_{k' \in K_l} \hat{N}_{jmkt} - 1 \right), l \in \{H, L\}$. I use the $\Delta \log \hat{N}_{jmt,-k}^H$ and $\Delta \log \hat{N}_{jmt,-k}^L$ as instruments for the actual change in local skill ratio. While constructing instruments for workers of occupation $k$, I exclude occupations similar to occupation $k$.\textsuperscript{32}

My identifying assumptions is $E \left( \Delta \xi_{jmtk} \Delta \log \hat{N}_{jmt,-k}^H \right) = 0$ and $E \left( \Delta \xi_{jmtk} \Delta \log \hat{N}_{jmt,-k}^L \right) = 0$, namely the residual preferences for unobserved amenities are uncorrelated with the changes in both high- and low-skilled populations predicted by initial job locations and changes in the value of time.

The assumptions would be violated if places with a high concentration of high-skilled jobs with a rising value of time are increasingly preferred by high-skilled workers, not due to the endogenously changing amenity level, but due to the changing taste or attitude for certain location-specific features such as cultural landmarks, architectures, etc.

One potential violation is if central cities tend to have a high concentration of high-skilled jobs with a rising value of time, but at the same time have a high concentration of existing location-specific features over which workers may have changing tastes. High-skilled workers may have moved to the central cities due to their increasingly stronger preferences for existing central city features such as cultural landmarks and architecture, not necessarily due to the endogenously changing amenities, which could lead to a bias in my estimation. As mentioned earlier, I account for the potentially changing taste for central city features by including a flexible control for location centrality and allow workers of different occupations to have arbitrarily changing tastes for such centrality.

The identification of $\beta_z$: To identify $\beta_z$, the preferences for rents, I use the setup described in the housing supply equation (6), in which $\Delta r_{jmt}$ is driven by growth in local residents interacted with existing housing stock in neighborhood $j$. I construct instruments for $\Delta r_{jmt}$ by interacting $\Delta \log \hat{N}_{jmt,-k}^H$, $\Delta \log \hat{N}_{jmt,-k}^L$ and $\Delta \log \left( \hat{N}_{jmt,-k}^L + \hat{N}_{jmt,-k}^H \right)$ with initial housing stock density $den_{jm}$ observed in the 1980 Census to identify preferences for rent. I standardize $den_{jm}$ with the mean and standard deviation of housing stock densities across neighborhoods.

The basis of identification is that initial housing density could potentially reduce the neighborhood-level housing supply elasticity, which would shift up rents. I assume that the elasticity of housing supply at a micro-geographic level partially depends on the neighborhood’s availability of developable land.\textsuperscript{33} If a neighborhood already has a high density of existing structures, the supply of new housing could be constricted (Baum-Snow and Han (2020)). I exploit the spatial variation in the initial housing density interacted with the predicted population changes to identify $\beta_z$.

The identifying assumptions are

$$E \left( \Delta \xi_{jmtk} \Delta \log \hat{N}_{jmt,-k}^l den_{jm} \right) = 0, l \in \{H, L\}, E \left( \Delta \xi_{jmtk} \Delta \log \left( \hat{N}_{jmt,-k}^L + \hat{N}_{jmt,-k}^H \right) den_{jm} \right) = 0,$$

and

$$E \left( \Delta \xi_{jmtk} den_{jm} \right) = 0,$$

which means that the residual change in preferences for unobserved the variation in the instrument, but not the identifying variation itself. I provide detailed derivation and explanation for why the size of $\hat{m}$ does not matter in the final estimates. See appendix D5.

\textsuperscript{32}I define similar occupations as occupations that belong to the same occupation group in the IPUMS Census/ACS data.

\textsuperscript{33}If a neighborhood’s topography is cut by bodies of water or hills, housing supply could also be constricted. These features, however, are considered as the unobserved cost shifters in my inverse housing supply equation.
amenities should not be correlated with initial housing density nor its interaction with predicted changes in population. A potential violation of the assumption would occur if places with a high level of existing housing development are increasingly attracting residents due to a taste change for the location-specific features of these locations. Similar to the identification of $\gamma_z$, one potential violation of the assumptions would occur if central cities have three things simultaneously: 1. high housing density, 2. increasingly attractive cultural landmarks, 3. a large concentration of jobs with a rising value of time. Workers may have moved to the central cities due to changing tastes for cultural amenities, while rents have been rising. This could lead the estimates to bias toward zero. Again, I account for the potentially changing taste for central city features by allowing workers to have arbitrarily changing taste for location centrality of each neighborhood.

To sum up, I list the moment conditions used for identifying $\mu_z, \gamma_z, \beta_z$:

$$E(\Delta\xi_{jmk} \tilde{E}_{t-1}(c_{jmk})) = 0,$$

$$E(\Delta\xi_{jmk} \Delta \log \tilde{N}_{jmt,-k}^{H}) = 0, l \in \{H, L\},$$

$$E(\Delta\xi_{jmk} \Delta \log \tilde{N}_{jmt,-k}^{L} \ln \text{den}_{jm}) = 0, l \in \{H, L\},$$

$$E(\Delta\xi_{jmk} \Delta \log (\tilde{N}_{jmt,-k}^{L} + \tilde{N}_{jmt,-k}^{H}) \ln \text{den}_{jm}) = 0,$$

$$E(\Delta\xi_{jmk} \ln \text{den}_{jm}) = 0.$$  

5.3 Housing supply

To estimate elasticities in the housing supply equation, I take the first difference:

$$\Delta r_{jmt} = \pi_1 \text{den}_{jm} \Delta \log \left( \sum_{k} \tilde{Y}_{mkt} N_{jmk} \right) + \pi_2 \text{den}_{jm} + \delta^r_{m} + \Delta \xi^r_{jmt}, \tag{10}$$

where $\pi_1 = \pi$ and $\pi_2 = \pi \Delta t$. $\delta^r_{m}$ is the MSA fixed effects after differencing the MSA/time fixed effects. For the identification of inverse housing supply elasticities, I need variation that drives the change in local aggregate income that is not correlated with $\Delta \xi_{jmt}$, which is neighborhood-level local housing supply shock (e.g. unobserved shocks to construction cost). I use the predicted log change in population of high-skilled, low-skilled and all workers $\Delta \log \tilde{N}_{jmt}^{H}, \Delta \log \tilde{N}_{jmt}^{L}$ and $\Delta \log (\tilde{N}_{jmt,-k}^{L} + \tilde{N}_{jmt,-k}^{H})$ to instrument for $\Delta \log \left( \sum_{k} \tilde{Y}_{mkt} N_{jmk} \right)$. The identifying assumption is that the unobserved housing supply shock is not correlated with predicted log changes in population.

To separately identify other parameters, I interact the instruments with housing stock density $\text{den}_{jm}$.

\[\text{Note that to identify the housing supply equation, instruments do not have to exclude data from workers in the occupation of interest as in the location demand equation, because the exclusion restriction only requires that instruments are uncorrelated with } \Delta \xi_{jmt}^r.\]
To sum up, I list the moment conditions used for identifying $\pi_1$, $\pi_2$:

$$E\left(\Delta \xi_{jm}^r \Delta \log \left(\hat{N}_{jm}^L + \hat{N}_{jm}^H\right) \text{den}_{jm}\right) = 0,$$
$$E\left(\Delta \xi_{jm}^r \Delta \log \hat{N}_{jm}^l \text{den}_{jm}\right) = 0, l \in \{H, L\},$$
$$E(\Delta \xi_{jm}^r \text{den}_{jm}) = 0.$$

I estimate the location demand and housing supply equations using two-step linear GMM estimators. I cluster the standard errors at the census tract level.

6 Model estimates

The model is estimated with data from all census tracts in all MSAs in the United States from the 1990 Census and 2007-2011 ACS data.\(^{35}\) Table 4 presents the summary statistics of the data I use.

To separately estimate $\gamma_z$ and $\beta_z$, I construct the instrumental variables based on the predicted change in high- and low-skilled workers’ log population. The first stage of these instrumental variables performs well.\(^{36}\) The instruments can predict the change in log skill ratio with very strong F-stats.\(^{37}\)

6.1 Estimates

Table 5 shows the estimates for $\mu_z$ are positive and significant for both high- and low-skilled workers, which means that workers with a higher value of time prefer neighborhoods with a shorter expected commute time. The estimate for high-skilled is 6.003, which means that one standard deviation rise in long-hour premium would lead to high-skilled workers having a 28% higher demand residential location that can save one hour of daily commute time.\(^{38}\) The estimate for low-skilled is 1.409, which means that one standard deviation rise in long-hour premium would lead to low-skilled workers having an 8% higher demand residential location that can save one hour of daily commute time.

Preference for endogenous amenities $\gamma_z$ is 1.617 for high-skilled workers and 0.345 for low-skilled workers, which means that census tracts with a 1% higher skill ratio would raise demand from high-

\(^{35}\)Location choice probabilities for each census tract by each occupation are imputed using procedures described in appendix section B1. To avoid zero probabilities, I add 1 to the number of imputed residents in each occupation-census tract cell before computing location choice probabilities.

\(^{36}\)Table A4 presents the first-stage results from regressing actual change in log skill ratio on predicted change in log skill ratio and change in log population of high- and low-skilled workers at the census tract level. The predicted change in the first-stage regression are generated for each census tract. The populations are calculated by summing over predicted populations over all occupations. In the actual estimation regression, each observation is at occupation/census tract level. The instruments used in the estimation are created by excluding the occupations in the occupation-group of the occupations in question.

\(^{37}\)I include the reduced-form results (regressing the change in location demand directly on the exogenous variables) in Table A5 in the appendix.

\(^{38}\)Recall that the long-hour premium is the marginal log weekly income gained from working an extra hour beyond a 40 hours/week threshold, and the expected commute time is scaled as the total commuting hours in a week. Assuming the average commuter goes to work 5 days a week, the weekly commute time should be 10 times the one-way commute time.
skilled workers 1.272 percentage point more than from low-skilled workers. Therefore, an exogenous shock that generates a rise in the local skill ratio in a neighborhood could lead to an endogenous demand response from high-skilled workers that is much larger than that from low-skilled workers, and thus further raise the local skill ratio in this neighborhood. This implies that some high-skilled workers may sort into the central city neighborhood without experiencing a value of time shock themselves, so long as central cities’ amenity levels increase.

The preference elasticity with respect to rent \( \beta_z \) for high-skilled is estimated to be 0.573 and 0.436 for low-skilled. Percentage-wise, the high-skilled are moderately more elastic with respect to rents. This is likely because high-skilled workers are more mobile and hence have smaller \( \sigma_z \). Recall from the model setup that the migration elasticities are inversely related to the standard deviation of logit component \( \sigma_z \). While each of the preference parameters is larger in magnitude for high-skilled workers, the difference in \( \beta_z \) is relatively modest. If I calculate the implied housing expenditure share for the high-skilled workers, it is about 10%. For low-skilled workers, it is about 31%.

The elasticity of rent with respect to housing demand shock is higher in neighborhoods with a higher housing stock density. The increase in elasticity with each standard deviation of housing density is 0.0984.

### 6.2 Amenity supply

In addition to the model estimates, I demonstrate that the local skill ratio is a driving force behind various types of local amenities. Table 6 presents the elasticities of the per-capita number of various local business establishments with respect to changes in local skill ratio. I use the predicted change in high- and low-skilled populations as IVs for the local skill ratio. I find that the per-capita count of local businesses is generally positively responsive to the shock to local skill ratio. The exception is the number of grocery stores in column 2. Also, the municipality-level violent crime and property crime rates are negatively affected by the rise in local skill ratio.

### 6.3 Robustness of estimation

I conduct several robustness checks to make sure the estimation is not driven by any particular features in the data or the specifications. The results are shown in Table 7.

First, I re-estimate the model by removing both amenities and rents and by removing amenities and rents one at a time. In column 1, I show the results in which amenities and rents are excluded from the specification. The estimates for \( \mu_z \) are much larger, which means without accounting for endogenous amenities change, the reduced-form relationship between the changing value of time and central city living would be biased upward, and such bias is particularly large for high-skilled workers.

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39 The implied housing expenditure share would be \( \frac{\sigma_z}{\mu_z} \).
40 I conduct the analysis at the census tract level. For each census tract, I compute the count of business establishments located within 1 mile of the census tract of interest. Meanwhile, I compute the total population within 1 mile of the census tract of interest. I then compute the per-capita count of business establishments by dividing the total count by population.

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workers. In column 2, I include amenities but not rents, and the estimates for $\gamma_z$ are much smaller than the main estimates. This is because amenities and rents co-move spatially, and the omitted negative effect of rents offsets the estimate for $\gamma_z$, if rents are omitted. In column 3, I include rents but not amenities, and the estimates for $\beta_z$ are positive, particularly for high-skilled workers. This is because variation in rent changes also picks up amenity changes, which workers, particularly the high-skilled, respond to positively.

Next, to ensure that my estimation is not driven by my use of the "long-hour premium" to measure the value of time, I replace the long-hour premium with alternative measurements of the value of time. First, if I use the dispersion of log wage by occupation as an alternative measurement, the results, shown in column 4, still similarly show that workers with rising dispersion of log wage are more likely to sort into neighborhoods closer to jobs. Next, I use the percentage of working long hours to proxy the value of time. The result, shown in column 5, is consistent with the low-skilled workers, but the sign flips for the high-skilled workers, though with less statistical significance.

Some may wonder whether the spatial sorting toward jobs is indeed driven by a desire to reduce commuting time. To check whether workers moving relatively closer to job locations indeed report a shorter commuting time, I replace the change in the long-hour premium with the change in observed commuting time measured at the occupation and MSA level. The coefficient of the interaction term would indicate whether workers who are moving closer to their jobs do indeed see a shorter or relatively slower growth of commuting time. The coefficient estimate shown in column 6 is consistent with that explanation.

Moreover, in the main specification, I specify high-skilled occupations as those in which at least 40% of the workers have college degrees. To show that the results are not entirely driven by such particular definition, I re-define high-skilled occupations using alternative definitions and estimate the model again using the new definitions. The results, shown in column 7 and 8, remain largely consistent with the results in the main specification.

7 Determinants of gentrification

Having estimated the model parameters, I now evaluate how much gentrification is explained by the rising value of time. The changing value of time directly affects people’s demand for central cities by making them choose shorter commute time, even with amenity levels held unchanged. Besides the direct effect, the changing location choice leads to changes in amenity and rent levels, which indirectly affect people’s demand for central cities. In this section, I evaluate the direct and indirect effects of the rising value of time on central cities’ gentrification. I evaluate gentrification by examining the changes in central cities’ skill ratios observed in the data and predicted by the model, separately. Lastly, I evaluate whether housing policies that lower rent growth would likely affect gentrification.
7.1 Direct effect of changing value of time

In the first exercise, I use the model to generate hypothetical location choices in 2010 that would have been made if only the value of time had changed, holding neighborhood amenities, rent, all other components constant at their 1990’s levels. The following equation gives the predicted location demand:

\[
\log(s_{jm,2010}) = \delta_{jm} + \delta_{mk,2010} + \log \left( \sum_{n \in J_m} \pi_{n'mk,t-1} \exp \left( -\mu_z v_{k,2010} \cdot c_{jnm} \right) \right) + \beta_z r_{jm,1990} + \gamma_z \log \left( \frac{N_{jm,1990}}{N_{jm,2010}} \right) + \theta_{k,1990} X_{jm} + \xi_{jm,1990}.
\]

To ensure that the predicted location choice probabilities add up to one for each occupation and each MSA, I adjust them accordingly with a normalizing constant \( \tilde{\delta}_{mk,2010} \).

All other components of the initial location demand are held fixed.

To quantify the gentrification of the central cities, I compute the change in the model-predicted relative log skill ratio in the central cities and compare it with the observed change. The relative log skill ratio is defined as the log skill ratio in the central cities minus the log skill ratio in the suburbs. I conduct this adjustment because skill ratios have increased in both central cities and suburbs, and the relative change in skill ratio captures the degree of spatial sorting between central cities and suburbs.

I define central cities as census tracts located within 3 miles or 5 miles of downtowns. Table 8 shows that around 6% to 7% of the relative skill ratio change in the central cities can be explained directly by the changing value of time. This result means that the rising value of time does contribute to the gentrification of the central cities, but the direct effect is small. In other words, if we were to adjust workers’ value of time from 1990’s to 2010’s level but hold everything else constant, we would see less than 10% of the gentrification of central cities that we actually see.

\[s_{jm,2010} = \frac{\exp(\log(s_{jm,1990}) - \log(\sum_{n' \in J_m} \pi_{n'mk,1990} \exp(-\mu_z v_{k,1990} c_{jnm}))) + \log(\sum_{n' \in J_m} \pi_{n'mk,1990} \exp(-\mu_z v_{k,2010} c_{jnm})))}{\sum_{n' \in J_m} \exp(\log(s_{jm,1990}) - \log(\sum_{n' \in J_m} \pi_{n'mk,1990} \exp(-\mu_z v_{k,1990} c_{jnm}))) + \log(\sum_{n' \in J_m} \pi_{n'mk,1990} \exp(-\mu_z v_{k,2010} c_{jnm})))}.
\]

Note that in this exercise, I hold MSAs’ population by occupation fixed at the 1990’s level. In other words, a change in occupation composition or spatial sorting across MSAs are not considered in the exercise. In Table A6 in the appendix, I re-do the exercise by allowing each MSA’s population by occupation to adjust to 2010’s observed levels. The predicted gentrification due to the direct effect of the value of time is considerably higher. This is because the number of high-skilled workers working in occupations with a rising value of time increased over time relative to other occupations. Therefore, even with the same change in central city choice probabilities, the magnitude of change in the relative skill ratio is larger. However, this numbers shown in the appendix may not be a good assessment of the role of the changing value of time because the overall increase in the number of high-skilled workers with a rising value of time is not a result of the rising value of time itself. The effect is boosted by a general change in labor market occupation mix or cross-city spatial sorting. This numbers shown in the appendix are, therefore, a likely overestimation of the role of the value of time.
7.2 Indirect effect through endogenous amenity and rent change

One important reason for the small magnitude of the model-predicted change in the last exercise is that it mutes the channel of endogenous amenity changes. Next, I allow the indirect effect of the changing value of time to operate through the endogenous amenity changes. In other words, I evaluate how much the gentrification of central cities is explained by the migration of workers as a result of amenities changes brought about by the movers, in addition to the migration directly due to the value of time change. For that purpose, I allow the local skill ratio, which approximates the endogenous levels of amenities, along with rent levels, to vary endogenously and change by the amount predicted by the shock to the value of time. Then, I compute a new set of predicted skill ratios for each census tract, according to the following location demand equation:

\[
\log (\hat{s}_{jmk,2010}) = \delta_{jmk} + \tilde{\delta}_{mk,2010} + \log \left( \sum_{n' \in J_m} \pi_{n'mk,t-1} \exp \left( -\mu_z v_{k,2010} \cdot c_{jn'm} \right) \right) + \gamma_z \log \left( \frac{\hat{N}_{jm,2010}^H}{\hat{N}_{jm,2010}^L} \right) - \beta_z \tilde{r}_{jm,2010} + \theta_{k,1990} X_{jm} + \xi_{jmk,1990}.
\]

To obtain the predicted amenity levels and rent levels, I regress the observed census tract-level change in log skill ratio and log rent on the change in log skill ratio and log rent, respectively, generated by the first exercise. The following are the fitted changes in log skill ratio and log rent:

\[
\Delta \log \left( \frac{\hat{N}_{jm,2010}^H}{\hat{N}_{jm,2010}^L} \right) = \hat{\alpha}_m^a \Delta \log \left( \frac{\hat{N}_{jm,2010}^H}{\hat{N}_{jm,2010}^L} \right)
\]

\[
\Delta \tilde{r}_{jm,2010} = \hat{\alpha}_{m0}^r + \hat{\alpha}_{1}^r \Delta \tilde{r}_{jm,2010}
\]

where \( \hat{\alpha}_m^a \) and \( \hat{\alpha}_{m0}^r \) are MSA fixed effects, and \( \hat{N}_{jm,2010}^H \) and \( \hat{N}_{jm,2010}^L \) are the census tract population predicted by the first exercise.

I take the fitted change in log skill ratio and log rent and use them to compute the predicted location demand in 2010. Since the migration elasticity with respect to amenity \( \gamma_z \) is much higher for high-skilled workers, adding the effect of endogenous amenity changes would draw in even more high-skilled workers in neighborhoods where the changes in skill ratios are already positively affected by the shock to the value of time.

Table 8 shows that once endogenous amenity and rents are adjusted, the predicted gentrification is much larger. This shows a large share of gentrifiers who migrated to the central cities are attracted

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43I regress the actual change in log skill ratio on the change in log skill ratio from the first exercise (allowing only the value of time to change). I then use the predicted value from the regression to construct the predicted local skill ratio in 2010. If the neighborhood’s observed skill ratio has risen, but the changing value of time does not predict any change, then the \( \Delta \log \left( \frac{\hat{N}_{jm,2010}^H}{\hat{N}_{jm,2010}^L} \right) \) would be zero. \( \Delta \log \left( \frac{\hat{N}_{jm,2010}^H}{\hat{N}_{jm,2010}^L} \right) \) only picks up variation in changes predicted by the shock to the value of time.
by the endogenously improved amenities, rather than an increased cost of commuting per se due to a rising value of time.\textsuperscript{44} However, the magnitude still only accounts for half of the full change of the central cities.\textsuperscript{45} This means that the gentrification of central cities cannot be entirely explained by the channels described in my paper. Other factors must also have played an important role.

### 7.3 Effect of lowering rent growth on gentrification

Could expansionary housing policies that lower rent growth have curbed some observed change in gentrification in central cities? To gauge the answer, I conduct another exercise in which rents are fixed at the 1990's level while allowing the value of time to change and amenities to adjust endogenously. The model predicts a similar and even slightly stronger degree of gentrification, shown in Table 8. The result suggests that the change in skill composition in central cities would not likely have been mitigated if rent growth were curbed by expansionary housing policies. The result stems from the fact that the estimates for $\beta_2$, the migration elasticities with respect to rents, for high- and low-skilled workers, are similar in magnitude. Therefore, lowering rent growth would lead to a similar rise in the low- and high-skilled populations in central cities, leading to a small counterfactual change in the ratio of high- and low-skilled residents. In the next section, however, I show that housing policies of lower rent growth could have a very large effect on mitigating welfare inequality.

One concern of the simple analysis of removing rent growth while maintaining amenity change is that in a general spatial equilibrium, amenity changes may be larger or smaller due to a counterfactual freeze in rent growth. If rents were held back in the 1990's level, workers might spatially sort in different ways, which may lead to a different counterfactual change in amenity levels. To re-compute a counterfactual level of amenities while changing just rents can be challenging in the given framework. However, I argue that such a confounding effect is not likely to be large enough to bias the exercise, given that the migration elasticities with respect to rents for high-skilled workers are quite similar to that for low-skilled workers.\textsuperscript{46}

\textsuperscript{44}To show the robustness of the decomposition result, I conduct further two exercises in which I alter the definitions of high-skilled occupations based on other college-share thresholds in the year 1990: 30% and 50%. I present the results of these exercises in appendix Table A6 and A7. The basic insights remain the same, except that with a more generous definition of skill occupation (1990 college share ≥ 30%), the predicted gentrification is generally smaller, whether direct or indirect. With a less generous definition of skilled occupation (1990 college share ≥ 50%), the predicted gentrification is larger, whether direct or indirect. This is an expected result given that gentrification has largely been driven by workers endowed with very high skill content. However, I prefer to use the number produced by the original definition of skilled occupation (1990 college share ≥ 40%). Such threshold is chosen such that the initial national skill ratio matches initial national college ratio, which makes my number more comparable with other papers which tend to study college ratio.

\textsuperscript{45}In Appendix E, I present a series of alternative MSA-level regressions to gauge the size of the full effect of the changing value of time (direct and indirect effects). The results lead to similar conclusion that the full effect accounts roughly half of the full change of the central cities.

\textsuperscript{46}The result of the exercise itself shows that skill ratio does not change much as a result of lowering rent growth, which confirms that the counterfactual level of amenities likely would not deviate much from the value used in the analysis in the first place.
8 Welfare analysis

In the final section, I analyze the effect of gentrification on welfare inequality through the lens of the model. I also discuss the effect of lowering rent growth on welfare inequality in the presence of other gentrifying forces.

I focus on the change in welfare inequality instead of the absolute welfare change because of a lack of a good measurement of change in the absolute levels of amenities. I measure amenities by examining the skill mix of neighborhoods. Although the change in local skill mix over time can be a good approximation of the change in relative amenities, it is not a measurement for the change in absolute amenities. From 1990 to 2010, the share of high-skilled workers increased nationwide, but such an absolute increase in skill share does not necessarily imply that amenities have improved everywhere. The differential change in skill mix by neighborhoods only captures the relative change. Without a good measurement of the change in absolute level of amenities, we can only focus on welfare inequality.

The prevailing concern about gentrification and the rising demand for housing in cities is that rising rents may negatively affect the welfare of low-skilled incumbents more than they affect that of high-skilled residents since housing constitutes a larger share of low-skilled residents’ budgets. Therefore, gentrification may exacerbate inequality between high- and low-skilled residents. However, the increase in welfare inequality could be overstated if the concurrently rising amenity levels compensate the low-skilled residents for the rising rents. If the newly created amenities mostly benefit the high-skilled residents, the rising amenity levels may even further exacerbate welfare inequality. Moreover, the rising value of time disproportionately affects the high-skilled workers, which could reduce the welfare of high-skilled workers more than that of low-skilled workers, offsetting some of the increase in welfare inequality.

I use the spatial equilibrium model to analyze the net welfare effects of the observed changes in the value of time, amenities, and rents on the welfare of low- and high-skilled workers. I then normalize the utility impact of these changes into an equivalent scale in log income for analysis.

8.1 Expected utility

Workers’ utility is a function of the log income, cost of commute time, as well as the amenity and rent levels. $\mu_z$ is the marginal utility of log income and the cost of commute time for skill level $z$. $\beta_z$ is the marginal disutility of log rents, and $\gamma_z$ is the marginal utility of amenities. The utility

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47 If neighborhood A’s share of high-skilled workers increased by more than neighborhood B, neighborhood A’s amenities would be expected to have become relatively better than neighborhood B’s amenities.

48 For this exercise, I abstract from the welfare effect of changing leisure inequality because doing so requires the marginal utility of leisure, which is difficult to estimate from a location choice model. Leisure inequality could be a force that narrows the welfare gap between high- and low-skilled workers due to the divergence of leisure times, documented by Aguiar and Hurst (2007). However, to make a precise statement on this matter, one must estimate how high-skilled and low-skilled workers value leisure differently. If high-skilled workers do not value leisure as much as low-skilled workers, then the welfare implication of leisure inequality may be small. Conversely, if high-skilled workers value leisure more than low-skilled workers do, welfare inequality may increase more if we take leisure into account.
level is defined as the following:

\[ V_{i,jnmt} = \mu_y y_{kt} - \mu_v v_{kt} c_{jnm} + \gamma_z \log \left( \frac{N^H_{jnt}}{N^L_{jnt}} \right) - \beta_z r_{jnt} + \xi_{jmt} + \varepsilon_{i,jnt}. \]

The expected utility for workers of occupation \( k \) working in neighborhood \( n \) is \( E(\max_j V_{i,jnmt}) \), which is equivalent to the expected utility of the top choice neighborhood for each worker within occupation \( k \). Since \( \varepsilon_{i,jnt} \) follows Type I Extreme Value, the expected utility becomes:

\[ E(U_{mk}) = \sum_{n \in J_m} \pi_{nmk} \ln \left( \sum_{j \in J_m} \exp (V_{jnmkt}) \right) \]

where the mean utility is \( V_{jnmkt} = \mu_y y_{kt} - \mu_v v_{kt} c_{jnm} + \gamma_z \log \left( \frac{N^H_{jnt}}{N^L_{jnt}} \right) - \beta_z r_{jnt} + \xi_{jmt}. \)

To start the exercise, I compute the expected utility in the initial year 1990 by using the observables from the 1990 data, where

\[ V_{jnmk,1990} = \mu_y y_{k1990} - \mu_v v_{k1990} c_{jnm} + \gamma_z \log \left( \frac{N^H_{jm1990}}{N^L_{jm1990}} \right) - \beta_z r_{jm1990} + \xi_{jm1990}. \]

Then, I proceed to compute the hypothetical utility level in 2010 by adjusting earnings, the value of time, rent, and amenities to 2010 levels. I normalize the expected utility measure by dividing it by the estimate of \( \mu_z \), the marginal utility log earnings. The change in normalized expected utility is thus measured in the unit of log earnings:

\[ \frac{E(\bar{U}_{mk,2010}) - E(U_{mk,1990})}{\mu_z} \]

I compute the change in the welfare gap between high- and low-skilled workers from 1990 to 2010 by applying the above equation for high- and low-skilled workers.

**Earnings**

First, I compute the expected utility if workers’ log earnings are changed to 2010 levels:

\[ \tilde{V}_{yjnmk,2010} = \frac{\mu_y y_{k2010}}{\text{earnings change}} - \mu_v v_{k1990} c_{jnm} + \gamma_z \log \left( \frac{N^H_{jm1990}}{N^L_{jm1990}} \right) - \beta_z r_{jm2010} + \xi_{jm1990}. \]

Table 9 Column 1 shows that the welfare gap due to a change in earnings increases from 0.7338 to 0.8162, which is 0.0825 log point.\(^{52}\)

\(^{49}\)Given neighborhood \( n \)'s share of jobs in occupation \( k \) in MSA \( m \) is \( \pi_{nmk} \), the overall expected utility in an MSA is given by a weighted average of the expected utilities conditional on work locations.\(^{50}\)\( \xi_{jm1990} \) can be computed from the location demand equation. It is the residual term in 1990.\(^{51}\)For example, if the normalized expected utility increases by 0.1 log point due to changing amenities, then the welfare impact of the changing amenities is equivalent to an increase of 0.1 log point in earnings.\(^{52}\)Since earning is calculated as the mean log earnings by occupation, the change in the welfare gap due to changes in earnings is equivalent to the changes in the earnings gap.
The value of time

To evaluate the impact of the changing value of time on welfare, I let the value of time adjust to 2010 levels. The expected utility is now the following:

\[
\hat{V}_{jnmk,2010}^{yw} = \mu_z y_{k2010} - \mu_z v_{km2010} c_{jnm} + \gamma_z \log \left( \frac{N_{jm1990}^H}{N_{jm1990}^L} \right) - \beta_z r_{jm1990} + \xi_{jmk1990}.
\]

This is expected to reduce welfare for the workers whose value of time rises over time, especially in cities where their job locations are highly concentrated. Table 9 Column 2 shows that the welfare gap increases by 0.0774 log points if the changes in the value of time are included, which is 6.19% smaller than the increase in the welfare gap due to earnings change alone.

Amenities and rents

Finally, I adjust amenities and rents to the 2010 levels.

The change in log skill ratio must be treated with caution because variation in skill ratio only measures amenity levels relative to each other. The preference parameter for amenities \( \gamma_z \) is also identified off the relative change in skill ratios over time. In the data, the skill ratio increases across the nation. However, the national rise in skill ratio does not necessarily represent an improvement in amenities nationwide. To ensure the measurement of amenity change captures relative amenities only, I compute the skill ratio for each neighborhood by holding the city-level population fixed in each skill category:

\[
\hat{N}_{jm2010}^H = \frac{N_{jm2010}^H}{N_{jm2010}^L} N_{im1990}^H, \quad \hat{N}_{jm2010}^L = \frac{N_{jm2010}^L}{N_{jm2010}^L} N_{im1990}^L.
\]

\[
\hat{V}_{jnmk,2010}^{yvar} = \mu_z y_{k2010} - \mu_z v_{km2010} c_{jnm} + \gamma_z \Delta \log \left( \frac{\hat{N}_{jm2010}^H}{\hat{N}_{jm2010}^L} \right) - \beta_z \Delta r_{jm1990} + \xi_{jmk1990}.
\]

Table 9 Column 3 shows that once amenities and rents are considered, the reduction in welfare inequality due to the changing value of time is entirely offset, and welfare inequality overshoots and exceeds the earnings gap. Welfare gap increases by 0.1197 log points, which is 45.20% larger than the increase in the earnings gap alone, entirely offsetting the reduction in the welfare gap induced by the changing value of time.

8.2 Effect of lowering rent growth on welfare inequality

Similar to the analysis in the previous section in which I evaluate the effect of holding back rent growth on observed gentrification, I evaluate the effect of curbing the rent growth on welfare inequality. I compare the welfare gap calculated in Column 4, with the gap calculated in Column 3 in Table 9. Column 3 shows the change in the welfare gap if all observables are adjusted to the 2010’s level, and Column 4 shows the change in the welfare gap if all observables except rents are adjusted.
Even though the change in amenities would still lead to an overall rise in welfare inequality, holding back rents to the initial level in 1990 would greatly mitigate the increase in the welfare gap.

It may seem counterintuitive that the effect of lowering rent growth on gentrification is small, while the effect is very large on welfare inequality. I obtain the contrasting result because the welfare effect of rents is normalized by $\mu_z$, whereas migration elasticity is $\beta_z$, which can be driven down by high migration friction. Hence, while $\beta_z$ are similar for high- and low-skilled workers, $\frac{\beta_z}{\mu_z}$ is much smaller for high-skilled workers compared to for low-skilled workers. This is intuitive since $\frac{\beta_z}{\mu_z}$ represents the budget share on rents, which is much higher for low-skilled workers than for high-skilled workers. Therefore, curbing rents would come as a much larger benefit for low-skilled workers.

9 Conclusion

Central city neighborhoods experienced a dramatic reversal of fortune in the past few decades. High-skilled workers increased their demand for housing in central city neighborhoods, which raised rents and amenity levels in these neighborhoods. I show that the rise in the value of time among high-skilled workers leads them to increasingly prefer living in central city neighborhoods to avoid long and costly commute time. These changing location preferences contribute to the rising demand for housing in central city locations. Furthermore, the effect of the rising value of time on housing demand leads to endogenous improvement in amenities, which leads to further sorting into central cities by high-skilled workers.

I estimate a spatial equilibrium model of residential choice to quantify the relative importance of the direct effect of rising value of time and the indirect effect of endogenous amenity change on gentrification. I show that the rising value of time has a modest direct role in gentrifying the central cities. However, the effect is substantially amplified by endogenous amenity change.

Based on the model framework, I evaluate the effect of the changing value of time, amenities, and rents on the welfare of high- and low-skilled workers. I show that welfare inequality between high- and low-skilled workers increases by more than the rise in earnings inequality.

Finally, I analyze the effect of lowering rent growth on gentrification and welfare inequality. I show that policies that lower rent growth would likely increase the population of both high- and low-skilled workers in central cities, but would not likely decrease the relative presence of high-skilled population in central cities. However, lowering rent growth could substantially mitigate the rise in welfare inequality between high- and low-skilled workers.

While this paper shows that the rise in the value of time contributes to gentrification, the mechanisms that cause the value of time to change remain open to future research. Besides, job locations are taken as given in this paper, and future research could examine how firms’ location decisions may respond to workers’ geographic re-sorting.
References


Figure 1: Income and home value ratio between central city and suburban neighborhoods

Notes: Central cities in these figures are census tracts that are located within 5 miles of the downtown in the respective MSAs defined in Holian and Kahn (2015). The values plotted are the mean income and home value of the census tracts located in the central cities and the mean income and home value of non-central city census tracts in the top 25 MSAs (defined by population ranking in 1990). The source of the data is the Decennial Census and ACS provided by NHGIS.

Figure 2: Change in skill ratio by distance to downtown

Notes: The graph shows a non-parametric plot between the change in log skill ratio and census tracts’ distances to downtowns in the top 25 most populous MSAs (defined by population ranking in 1990). The source of the data is the Decennial Census and ACS provided by NHGIS. The solid line represents the change in log skill ratios from 1990 to 2010. The long dashed line represents the change in log skill ratios from 1990 to 2000, and the short dashed line represents the change from 2000 to 2010.
Figure 3: Residential and work location sorting by skill

a) Residential location in 1990 and 2010
b) Work location in 1990 and 2010

Notes: Figure a is a binned scatterplot between the shares of residents living in central city neighborhoods in 1990 and in 2010. Figure b is a binned scatterplot between the share of jobs located in central city locations in 1990 and in 2010. The sample used in each figure is divided into high- and low-skilled occupations. High-skilled occupations are defined as occupations in which more than 40% of the workers have college degrees in 1990. The employment data come from ZCBP at zip code level. Central cities are defined as census tracts and zip codes with centroids within 5-mile radius of the downtown pin. I use the sample from the most populous 25 MSAs to produce these graphs. I use the 1994 Zip Code Business Patterns (ZCBP) to approximate work location in 1990. Residential location data come from both IPUMS and NHGIS Census data. Details are described in the data section. Square dots represent binned scatterplot of data in high-skilled occupations, and circle dots represent binned scatterplot of data in low-skilled occupations. The estimated slopes and the difference in slopes in the underlying regressions are reported, and the robust standard errors are reported in the parentheses.
Figure 4: Rising presence of high-skilled residents in central cities occurs in previously poor neighborhoods

Notes: These figures show the increase of high-skilled residents in central cities by neighborhood income quintile as a fraction of total increase in high-skilled residents in central cities. I use the sample of the most populous 25 MSAs. Central cities are defined as census tracts located within 5 miles of city centers (Holian and Kahn (2015)). The purpose of the figures is to show that gentrification of central cities mainly occurred in neighborhoods which were previously low-income. Income ranking in subfigure a) is based on income levels in 1980. Subfigure b) is based on income levels in 2000.

Figure 5: Changing working hours and commute time by wage decile (1980-2010)

Notes: The data come from IPUMS Decennial Census and ACS data in 1980 and 2010 (2007-2011 ACS). In a), I compute the change in percent of workers of working at least 50 hours per week. The sample I use includes workers that are between 25 and 65 of age, males, and working at least 30 hours per week. I include only male in the sample to ensure that the changing female labor force participation does not distort the statistics. In b), I compute the change in log commute time reported in the Census/ACS data. The sample includes workers that are between 25 and 65 of age, males, working at least 30 hours per week and living in the most populous 25 MSAs in the US.
Table 1: Relationship between local skill ratio and supply of local amenities

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<td>Grocery stores per 1000 residents</td>
<td>Gyms per 1000 residents</td>
<td>Personal serv. estab. per 1000 residents</td>
<td>Property crime per 1000 residents</td>
<td>Violent crime per 1000 residents</td>
</tr>
<tr>
<td>Δ ln (skill ratio)</td>
<td>0.284</td>
<td>0.0129</td>
<td>0.454</td>
<td>0.528</td>
<td>-0.495</td>
<td>-0.597</td>
</tr>
<tr>
<td></td>
<td>(0.0273)</td>
<td>(0.0254)</td>
<td>(0.0224)</td>
<td>(0.0265)</td>
<td>(0.112)</td>
<td>(0.0929)</td>
</tr>
<tr>
<td>MSA fixed-effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>19,291</td>
<td>19,291</td>
<td>19,291</td>
<td>19,291</td>
<td>1,870</td>
<td>1,870</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1143</td>
<td>0.1246</td>
<td>0.1072</td>
<td>0.1751</td>
<td>0.2836</td>
<td>0.4849</td>
</tr>
</tbody>
</table>

Notes: Results shown above are OLS regressions, with sample from all MSAs. Each observation for column 1 – 4 is at the census tract level. For each census tract, I sum up all the relevant business establishments located within a 1-mile radius of zip code centroids. Then, I sum up the population in census tracts located within 1 mile, and compute the count of establishments per 1000 residents. The skill ratio is computed as the ratio of the number of workers in high-skilled occupations and the number of workers in low-skilled occupations summed over all census tracts within 1 miles of each census tract. Each observation for column 5 – 6 is a municipality. To compute log crime rate, I add 0.1 to avoid taking log over zero crime rate. To compute skill ratio for 5 – 6, I match census tracts to municipalities, and compute the overall skill ratio using variables summed over across census tracts matched to municipalities. Robust standard errors are reported in parentheses.
Table 2: Workers in increasingly long-hour occupations increasingly live the central cities and have slower growth in commuting time

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \ln$ (share in central city)</th>
<th>$\Delta \ln$ (reported commuting time)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>Largest 10 MSAs</td>
<td>Largest 25 MSAs</td>
</tr>
<tr>
<td>$\Delta \ln$ (pct long-hour)</td>
<td>0.244 (0.081)</td>
<td>0.208 (0.057)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,140</td>
<td>5,347</td>
</tr>
<tr>
<td>Fixed-Effects Tabulation</td>
<td>MSA</td>
<td>MSA</td>
</tr>
<tr>
<td>S.E.</td>
<td>Cluster at MSA</td>
<td>Cluster at MSA</td>
</tr>
</tbody>
</table>

Notes: Results shown above are OLS regressions, with tabulated cells by MSA and occupation. I compute the share in central city by computing the percentage of workers in each occupation in each MSA who live within 5-mile radius of downtown pin (Holian and Kahn (2015)). The percentage of long hour is defined as the share of workers within each occupation who work at least 50 hours a week. The regressions are conducted by taking the first difference between data in 2010 and 1990. MSA fixed effects are included. Standard errors are clustered at MSA level.

Table 3: Reduced-form relationship between long-hour premium and long-hour worked, central city sorting, and commuting time

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \ln$ (pct long-hour)</th>
<th>$\Delta \ln$ (share in central city)</th>
<th>$\Delta \ln$ (reported commuting time)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>Largest 10 MSAs</td>
<td>Largest 25 MSAs</td>
<td>all MSAs</td>
</tr>
<tr>
<td>$\Delta$ LHP</td>
<td>13.62 (4.092)</td>
<td>8.13 (3.76)</td>
<td>6.61 (2.66)</td>
</tr>
<tr>
<td>Observations</td>
<td>214</td>
<td>2,140</td>
<td>5,347</td>
</tr>
<tr>
<td>Fixed-Effects Tabulation</td>
<td>N/A</td>
<td>MSA</td>
<td>MSA/occupation</td>
</tr>
<tr>
<td>S.E.</td>
<td>Robust</td>
<td>Cluster at MSA</td>
<td>Cluster at MSA</td>
</tr>
</tbody>
</table>

Notes: Results shown above are OLS regressions, with tabulated cells. In column 1, I regression the change in the percentage of working long hours on the change in long-hour premium (LHP) across occupations, with each observation a tabulation of occupation. From column 2 to 7, I compute the share in central city by computing the percentage of workers in each occupation in each MSA who live within 5-mile radius of downtown pin (Holian and Kahn (2015)). The percentage of long hour is defined as the share of workers within each occupation who work at least 50 hours a week. The regressions in column 2-7 are conducted by taking the first difference between data in 2010 and 1990, with each observation an MSA/occupation tabulation. LHP denotes long-hour premium. MSA fixed effects are included. Standard errors are clustered at MSA level.
Table 4: Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Obs.</th>
<th>Mean</th>
<th>SD</th>
<th>min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-hour premium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>214</td>
<td>0.0145</td>
<td>0.00466</td>
<td>0.00353</td>
<td>0.0349</td>
</tr>
<tr>
<td>2010</td>
<td>214</td>
<td>0.0141</td>
<td>0.00558</td>
<td>-0.00563</td>
<td>0.0355</td>
</tr>
<tr>
<td>Change</td>
<td>214</td>
<td>-0.000459</td>
<td>0.00551</td>
<td>-0.0238</td>
<td>0.0197</td>
</tr>
<tr>
<td>Long-hour premium (high-skilled)</td>
<td>1990</td>
<td>58</td>
<td>0.0136</td>
<td>0.00429</td>
<td>0.00481</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>58</td>
<td>0.0143</td>
<td>0.00632</td>
<td>0.00368</td>
</tr>
<tr>
<td></td>
<td>Change</td>
<td>58</td>
<td>0.000685</td>
<td>0.00473</td>
<td>-0.0117</td>
</tr>
<tr>
<td>Long-hour premium (low-skilled)</td>
<td>1990</td>
<td>156</td>
<td>0.0149</td>
<td>0.00477</td>
<td>0.00353</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>156</td>
<td>0.0140</td>
<td>0.00531</td>
<td>-0.00563</td>
</tr>
<tr>
<td></td>
<td>Change</td>
<td>156</td>
<td>-0.000885</td>
<td>0.00573</td>
<td>-0.0238</td>
</tr>
<tr>
<td>Log skill ratio</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>42,346</td>
<td>-1.112</td>
<td>0.577</td>
<td>-4.311</td>
<td>0.747</td>
</tr>
<tr>
<td>2010</td>
<td>42,346</td>
<td>-0.982</td>
<td>0.626</td>
<td>-3.910</td>
<td>1.148</td>
</tr>
<tr>
<td>Change</td>
<td>42,346</td>
<td>0.130</td>
<td>0.359</td>
<td>-1.651</td>
<td>2.367</td>
</tr>
<tr>
<td>Log rent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>42,346</td>
<td>6.492</td>
<td>0.429</td>
<td>5.107</td>
<td>7.421</td>
</tr>
<tr>
<td>2010</td>
<td>42,346</td>
<td>6.653</td>
<td>0.424</td>
<td>4.595</td>
<td>7.601</td>
</tr>
<tr>
<td>Change</td>
<td>42,346</td>
<td>0.160</td>
<td>0.264</td>
<td>-2.404</td>
<td>2.479</td>
</tr>
<tr>
<td>Log restaurants per 1000 residents</td>
<td>1990</td>
<td>19,291</td>
<td>-5.194</td>
<td>1.609</td>
<td>-9.861</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>19,291</td>
<td>-5.081</td>
<td>1.538</td>
<td>-10.815</td>
</tr>
<tr>
<td></td>
<td>Change</td>
<td>19,291</td>
<td>0.114</td>
<td>0.931</td>
<td>-9.242</td>
</tr>
<tr>
<td>Log grocery stores per 1000 residents</td>
<td>1990</td>
<td>19,291</td>
<td>-5.929</td>
<td>1.454</td>
<td>-10.077</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>19,291</td>
<td>-6.128</td>
<td>1.381</td>
<td>-10.815</td>
</tr>
<tr>
<td></td>
<td>Change</td>
<td>19,291</td>
<td>0.199</td>
<td>0.877</td>
<td>-8.756</td>
</tr>
<tr>
<td>Log gyms per 1000 residents</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>19,291</td>
<td>-7.984</td>
<td>1.645</td>
<td>-11.976</td>
<td>2.767</td>
</tr>
<tr>
<td>Change</td>
<td>19,291</td>
<td>0.450</td>
<td>0.800</td>
<td>-8.973</td>
<td>4.725</td>
</tr>
<tr>
<td>Log personal services per 1000 residents</td>
<td>1990</td>
<td>19,291</td>
<td>-6.673</td>
<td>1.749</td>
<td>-11.432</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>19,291</td>
<td>-6.789</td>
<td>1.611</td>
<td>-10.927</td>
</tr>
<tr>
<td></td>
<td>Change</td>
<td>19,291</td>
<td>-0.116</td>
<td>0.965</td>
<td>-10.882</td>
</tr>
<tr>
<td>Log violent crime rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>1,870</td>
<td>1.257</td>
<td>1.023</td>
<td>-2.303</td>
<td>4.150</td>
</tr>
<tr>
<td>2010</td>
<td>1,870</td>
<td>0.878</td>
<td>0.947</td>
<td>-2.303</td>
<td>4.177</td>
</tr>
<tr>
<td>Change</td>
<td>1,870</td>
<td>-0.378</td>
<td>0.746</td>
<td>-5.133</td>
<td>3.204</td>
</tr>
<tr>
<td>Log property crime rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>1,870</td>
<td>3.797</td>
<td>0.598</td>
<td>-2.303</td>
<td>5.843</td>
</tr>
<tr>
<td>2010</td>
<td>1,870</td>
<td>2.821</td>
<td>1.043</td>
<td>-2.303</td>
<td>6.763</td>
</tr>
<tr>
<td>Change</td>
<td>1,870</td>
<td>-0.976</td>
<td>0.826</td>
<td>-6.367</td>
<td>4.209</td>
</tr>
</tbody>
</table>

Notes: The table shows the summary statistics for the long-hour premium (high- and low-skilled), skill ratio, rent, and various amenities and crime. For the long-hour premium, each observation is an occupation. High-skilled occupations are those with at least 40% college degree in 1990 Census, and low-skilled occupations are the rest of the occupations. Skill ratio and rents are at the census tract level in 1990 and 2010. Skill ratio and the amenities (restaurant, grocery, gym, personal services) are at the census tract level as well. For each census tract, I sum up all the relevant business establishments located within a 1-mile radius, and I sum up the population in census tracts located within 1 mile, and compute the count of establishments per 1000 residents. Violent and property crime rates are at municipality level.
Table 5: Estimates of model parameters

<table>
<thead>
<tr>
<th>Panel A: Worker’s residential location demand</th>
<th>Panel B: Rent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commute cost ($\mu$) High-skilled 6.003 (0.840)</td>
<td>Housing demand $\times$ housing stock density ($\pi_1$) 0.0984 (0.0166)</td>
</tr>
<tr>
<td>Low-skilled 1.409 (0.624)</td>
<td>Housing stock density ($\pi_2$) 0.0181 (0.00328)</td>
</tr>
<tr>
<td>Amenity ($\gamma$) High-skilled 1.617 (0.130)</td>
<td></td>
</tr>
<tr>
<td>Low-skilled 0.345 (0.102)</td>
<td></td>
</tr>
<tr>
<td>Rent ($-\beta$) High-skilled -0.573 (0.151)</td>
<td></td>
</tr>
<tr>
<td>Low-skilled -0.436 (0.129)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Model estimated using occupation/census tract cell data from 1990 to 2010. Number of cells used is 8,755,373. The number of workers in each occupation/MSA in 1990 is used as analytical weight. I control for total expected commute (using expected commute time to jobs unrelated to workers' occupations) and the change in expected commute time, and I allow the coefficients on total expected commute and the change in expected commute time to vary by occupation. Standard errors are clustered at census tract level. Estimation detail can be found in the text.

Table 6: Estimates for amenity supply equations

<table>
<thead>
<tr>
<th>Dependent variable: $\Delta \ln$ (measurement of the selected amenity)</th>
<th>(1) Restaurants per 1000 residents</th>
<th>(2) Grocery stores per 1000 residents</th>
<th>(3) Gyms per 1000 residents</th>
<th>(4) Personal serv. estab. per 1000 residents</th>
<th>(5) Property crime per 1000 residents</th>
<th>(6) Violent crime per 1000 residents</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln$ (skill ratio)</td>
<td>0.518 (0.101)</td>
<td>-0.191 (0.0936)</td>
<td>1.097 (0.0829)</td>
<td>0.858 (0.0946)</td>
<td>-2.701 (1.040)</td>
<td>-3.007 (1.216)</td>
</tr>
<tr>
<td>MSA fixed-effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>19,291</td>
<td>19,291</td>
<td>19,291</td>
<td>19,291</td>
<td>1,870</td>
<td>1,870</td>
</tr>
</tbody>
</table>

Notes: Results shown above are GMM/IV regressions, with sample from all MSAs. I use the change in log number of high-skilled workers and change in log number of low-skilled workers predicted by expected commute time and change of value of time as instrumental variables for the change in skill ratio. Each observation for column 1 – 4 is at census tract level. For each census tract, I sum up all the relevant business establishments located within 1-mile radius. Then, I sum up the population in census tracts located within 1 mile, and compute the count of establishments per 1000 residents. The skill ratio is computed as the ratio of the number of workers in high-skilled occupations and the number of workers in low-skilled occupations summed over all census tracts within 1 miles of each census tract. Each observation for column 5 – 6 is a municipality. To compute log crime rate, I add 0.1 to avoid taking log over zero crime rate. To compute skill ratio for 5 – 6, I match census tracts to municipalities, and compute the skill ratio using variables summed over across census tracts matched to municipalities. Robust standard errors are reported.
Table 7: Robustness tests with alternative model specifications

<table>
<thead>
<tr>
<th>Commute only</th>
<th>Commute and amenities only</th>
<th>Commute and rents only</th>
<th>Alternative value of time measure</th>
<th>Sorting by observed commuting time</th>
<th>Alternative definition for high-skilled workers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Worker's location demand</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residual log</td>
<td>Pct of long hour Col&gt;30%</td>
<td>Col&gt;50%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>earnings dispersion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(1)  |  (2)  |  (3)  |  (4)  |  (5)  |  (6)  |  (7)  |  (8)  |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ High-skilled</td>
<td>20.664</td>
<td>10.463</td>
<td>11.243</td>
<td>0.0766</td>
<td>-0.0496</td>
<td>0.0997</td>
<td>6.184</td>
</tr>
<tr>
<td>Low-skilled</td>
<td>3.290</td>
<td>2.742</td>
<td>4.167</td>
<td>0.0320</td>
<td>0.175</td>
<td>0.0396</td>
<td>2.128</td>
</tr>
<tr>
<td>$\gamma$ High-skilled</td>
<td>-</td>
<td>1.112</td>
<td>1.587</td>
<td>1.652</td>
<td>1.645</td>
<td>1.558</td>
<td>1.283</td>
</tr>
<tr>
<td>Low-skilled</td>
<td>-</td>
<td>-0.357</td>
<td>0.334</td>
<td>0.345</td>
<td>0.353</td>
<td>0.284</td>
<td>0.605</td>
</tr>
<tr>
<td>$-\beta$ High-skilled</td>
<td>-</td>
<td>-</td>
<td>0.581</td>
<td>-0.541</td>
<td>-0.585</td>
<td>-0.579</td>
<td>-0.536</td>
</tr>
<tr>
<td>Low-skilled</td>
<td>-</td>
<td>-</td>
<td>0.0984</td>
<td>-0.427</td>
<td>-0.420</td>
<td>-0.437</td>
<td>-0.479</td>
</tr>
</tbody>
</table>

Notes: Each model specification is estimated using occupation/census tract cell data from 1990 to 2010. The number of workers in each occupation/MSA in 1990 is used as analytical weight. I control for total expected commute (using expected commute time to jobs unrelated to workers’ occupations) and the change in occupation-specific expected commuting time, and I allow the coefficients on these controls to vary by occupation. Standard errors are clustered at census tract level. Column 1 shows results from estimation with only commuting cost. Column 2 shows results with amenity change but no rent changes. Column 3 shows results with only rent changes but no amenity change. Column 4 and 5 replace long-hour premium with log earnings dispersion and percentage of working long hours respectively as proxies for the value of time. Column 6 replaces long-hour premium with observed commuting time for each occupation each year in each MSA. Column 7 – 8 show results from estimation using alternative definitions of high-skilled occupations (using 30% or 50% as thresholds rather than 40%).
Table 8: Gentrification decomposition – relative log skill ratio

<table>
<thead>
<tr>
<th>Dist. To downtown</th>
<th>Largest 25 MSAs</th>
<th>Largest 50 MSAs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ Value</td>
<td>Δ Value</td>
</tr>
<tr>
<td></td>
<td>of time</td>
<td>of time +</td>
</tr>
<tr>
<td></td>
<td></td>
<td>endogenous Δ</td>
</tr>
<tr>
<td></td>
<td></td>
<td>amenity + Δ</td>
</tr>
<tr>
<td>Actual</td>
<td>0.305</td>
<td>0.305</td>
</tr>
<tr>
<td>3 miles</td>
<td>0.0192</td>
<td>0.120</td>
</tr>
<tr>
<td>%</td>
<td>6.30%</td>
<td>39.34%</td>
</tr>
<tr>
<td>Actual</td>
<td>0.235</td>
<td>0.235</td>
</tr>
<tr>
<td>5 miles</td>
<td>0.0168</td>
<td>0.102</td>
</tr>
<tr>
<td>%</td>
<td>7.15%</td>
<td>43.40%</td>
</tr>
</tbody>
</table>

Notes: The results shown in this table show the comparison between actual changes in relative skill ratio and model-predicted changes in relative skill ratio. Relative skill ratio is defined as ratio between skill ratio (residents in high-skilled occupations/residents in low-skilled occupations) in central cities and skill ratio in the suburbs. I use varying definitions of central city, and sample from largest 25 MSAs and largest 50 MSAs. Actual changes in relative skill ratio are computed using observed spatial data by occupation. The values shown are the mean change in skill ratio weighted by MSAs’ population.

Table 9: Welfare inequality decomposition

<table>
<thead>
<tr>
<th>Changes allowed</th>
<th>Earnings</th>
<th>Earnings &amp; commute cost</th>
<th>Earnings &amp; commute cost &amp; amenities &amp; rents</th>
<th>Earnings &amp; commute cost &amp; amenities (no Δ in rents)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Welfare gap in</td>
<td>0.7338</td>
<td>0.7338</td>
<td>0.7338</td>
<td>0.7338</td>
</tr>
<tr>
<td>1990</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Welfare gap in</td>
<td>0.8162</td>
<td>0.8111</td>
<td>0.8535</td>
<td>0.8249</td>
</tr>
<tr>
<td>2010</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ in welfare gap</td>
<td>0.0825</td>
<td>0.0774</td>
<td>0.1197</td>
<td>0.0912</td>
</tr>
<tr>
<td>Effect on Δ in</td>
<td>---</td>
<td>-0.0051</td>
<td>+0.0373</td>
<td>+0.0087</td>
</tr>
<tr>
<td>welfare gap</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effect as a %</td>
<td>---</td>
<td>-6.19%</td>
<td>+45.20%</td>
<td>+10.60%</td>
</tr>
</tbody>
</table>

Notes: Welfare is computed as the mean expected utility of workers in each occupation in 1990 and 2010, weighted by the number of workers in each occupation in each MSA. Welfare gap is the difference between expected utility for high-skilled workers and low-skilled workers rescaled by the marginal utility of log earnings μ. I normalize the welfare gap in 1990 to its earnings gap. High-skilled workers are workers in high-skilled occupations, which are defined as occupations in which more than 40% of the sample hold college degree in 1990 Census. The last row “effect on Δ in welfare gap” denotes the difference between the change in welfare gap and the change in earnings gap. This is shown to highlight how each factor adds or offsets the widening welfare gap.
Online Appendix

The Rising Value of Time and the Origin of Urban Gentrification
Yichen Su

The appendix contains a few sections. Section A presents some extra details regarding my spatial equilibrium model. Section B contains the data appendix, in which I discuss how I obtain census tract residential locations, zip-code level job locations, and the procedure through which I obtain the travel time matrix. Section C describes some extra descriptive statistics that augment the analysis in the main text. Section D contains the estimation appendix, in which I discuss the estimation of long-hour premium and various validation tests for long-hour premium, lasso analysis of occupation characteristics, alternative measurement of the value of time, and some technical details of the estimation procedure. Section E contains a set of alternative exercises that shed light on the full effect of the changing value of time on gentrification.

A Model

A.1 Worker’s location choice problem

This section details the solution procedure that derives workers’ indirect utility function, given location characteristics (rents and amenities) and workers’ occupation, from the basic assumption of Cobb-Douglas utility function.

The utility-maximization problem is

$$\max_{C, H} U(C, H, A_{jmt}, c_{jnmt}) = C^\theta H^{1-\theta} A_{jmt}^{\tilde{\gamma}} \exp (-\tilde{\omega} c_{jnmt}) \exp (\sigma^i_c_{jmt})$$

subject to budget constraint

$$C + R_{jmt}H = \exp(y_{0lt} + v_{lt} (T - c_{jnmt}))$$

By Cobb-Douglas functional form, the demand for tradable consumption and housing services is (let $I$ denote weekly earnings):

$$C^* = \theta I$$

$$H^* = \frac{1-\theta}{R_{jmt}} I$$

The log-transformed partial indirect utility is then:

$$V_{i,jnmt} = \theta \log (\theta I) + (1-\theta) \log \left(\frac{1-\theta}{R_{jmt}} I\right) - \tilde{\omega} c_{jnmt} + \tilde{\gamma} a_{jmt} + \tilde{\gamma} k_{jmt} + \sigma^i_{c_{jmt}}.$$ 

The equation can be simplified with some algebra manipulation and by substitute $I$ with the earnings
\[
V_{i,jnmt} = \theta \log(\theta) + (1 - \theta) \log(1 - \theta) + (y_{0kt} + v_{kt}(T - c_{jnmt})) \\
- (1 - \theta) \log(R_{jmt}) - \tilde{\omega}_t c_{jnmt} + \tilde{\gamma}_k a_{jmt} + \tilde{\gamma}_k' c_{jmt} + \sigma \varepsilon_{i,jmt}
\]

I then re-normalize the indirect utility function by dividing the entire utility function by \(\sigma_k\), so that I can interpret the all coefficients as migration elasticities.

\[
V_{i,jnmt} = \frac{1}{\sigma_k} (\theta \log(\theta) + (1 - \theta) \log(1 - \theta)) \\
+ \frac{1}{\sigma_k} (y_{0kt} + v_{kt}(T - c_{jnmt})) - \frac{(1 - \theta) \log(R_{jmt})}{\sigma_k} \\
- \frac{\tilde{\omega}_t}{\sigma_k} c_{jnmt} + \frac{\tilde{\gamma}_k}{\sigma_k} a_{jmt} + \frac{\tilde{\gamma}_k'}{\sigma_k} c_{jmt} + \varepsilon_{i,jmt}
\]

I simplify the above equation by combining terms. By doing so, I arrive at the following equation which is the one presented in the main body of the paper.

\[
V_{i,jnmt} = \delta_{kt} - \mu_k v_{kt} c_{jnmt} - \omega_{kt} c_{jnmt} - \beta_k r_{jmt} + \gamma_k a_{jmt} + \gamma_k' c_{jmt} + \varepsilon_{i,jmt}
\]

Each coefficient is written in terms of the underlying parameters:

\[
\delta_{kt} = \frac{1}{\sigma_k} (\theta \log(\theta) + (1 - \theta) \log(1 - \theta)) + \frac{1}{\sigma_k}(y_{0kt} + v_{kt}T) \\
\mu_k = \frac{1}{\sigma_k} \\
\beta_k = \frac{1 - \theta}{\sigma_k} \\
\gamma_k = \frac{\tilde{\gamma}_k}{\sigma_k} \\
\omega_{kt} = \frac{\tilde{\omega}_t}{\sigma_k}
\]

A.2 Worker’s problem with leisure choice

In this section, I derive a utility specification with leisure as a choice. I show that such specification is empirically equivalent to the original specification used in the paper. I solve the problem in two steps. In the first step, I solve the utility-maximization problem holding leisure hours fixed, making the problem a standard utility-maximization of the Cobb-Douglas utility function. Once I obtain the partial indirect utility function given each level of leisure, I then solve for optimal leisure hours and the indirect utility function. Finally, I normalize the indirect utility function with the standard deviation of the idiosyncratic component of worker’s preference.
Step 1: Solve for partial indirect utility given leisure consumption.

Given the workers’ utility function of $C, H$ and $L$, I fix $L$ first and solve for $C$ and $H$ first. Let $\theta_L = 1 - \theta_C - \theta_H$.

$$\max_{C,H} U(C, H, L, A_{jmt}, c_{jmt}) = C^{\theta_C} H^{\theta_H} L^{\theta_L} \frac{\bar{A}_{jmt}}{\sigma_k} \exp(-\tilde{\omega}_t c_{jmt}) \exp(\sigma_k \varepsilon_{i,jmt})$$
subject to budget constraint

$$C + R_{jmt} H = \exp(y_{0kt} + v_{kt} (T - c_{jmt}))$$

By Cobb-Douglas functional form, the demand for tradable consumption and housing services is (let $I$ denote weekly earnings):

$$C^* = \frac{\theta_C}{\theta_C + \theta_H} I$$
$$H^* = \frac{\theta_H}{R_{jmt} \theta_C + \theta_H} I.$$ 

The log-transformed partial indirect utility given leisure consumption $L$ is then:

$$V_{i,jmt}(L) = \theta_C \log \left( \frac{\theta_C}{\theta_C + \theta_H} I \right) + \theta_H \log \left( \frac{\theta_H}{R_{jmt} \theta_C + \theta_H} I \right) + \theta_L \log (L) - \tilde{\omega}_t c_{jmt} + \tilde{\gamma}_k a_{jmt} + \tilde{\gamma}_k \zeta_{jmt} + \sigma_k \varepsilon_{i,jmt}.$$ 

The equation can be simplified with some algebra manipulation and by substitute $I$ with the earnings equation:

$$V_{i,jmt}(L) = \theta_C \log \left( \frac{\theta_C}{\theta_C + \theta_H} \right) + \theta_H \log \left( \frac{\theta_H}{R_{jmt} \theta_C + \theta_H} \right) + (\theta_C + \theta_H) (y_{0kt} + v_{kt} (T - c_{jmt})) - \theta_H \log (R_{jmt}) - \theta_L \log (L) - \tilde{\omega}_t c_{jmt} + \tilde{\gamma}_k a_{jmt} + \tilde{\gamma}_k \zeta_{jmt} + \sigma_k \varepsilon_{i,jmt}.$$ 

Step 2: Solve for optimal leisure choice and the indirect utility function.

The maximization of the second step is the following.

$$\max_L V_{i,jmt}(L)$$

It can be seen that leisure consumption increases utility through the term $\theta_L \log (L)$. But higher leisure hours means lower working hours, which reduces log earnings. Optimal leisure is obtained by solving the tradeoff problem.

A simple first-order condition leads to:

$$L^* = \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}}$$
Substituting optimal leisure back into the partial indirect utility, I obtain the indirect utility function.

\[
V_{i,jnmt} = \theta_C \log \left( \frac{\theta_C}{\theta_C + \theta_H} \right) + \theta_H \log \left( \frac{\theta_H}{\theta_C + \theta_H} \right) \\
+ (\theta_C + \theta_H) \left( y_{0kt} + v_{kt} \left( T - \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}} c_{jnmt} \right) \right) \\
- \theta_H \log \left( R_{jmt} \right) + \theta_L \log \left( \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}} \right) - \tilde{\omega}_t c_{jnmt} + \tilde{\gamma}_k a_{jmt} + \tilde{\gamma}_k \xi_{jmt} + \sigma_k \varepsilon_{i,jmt}
\]

I then re-normalize the indirect utility function by dividing the entire utility function by \( k \), so that I can interpret all the coefficients as migration elasticities.

\[
V_{i,jnmt} = \frac{1}{\sigma_k} \left( \theta_C \log \left( \frac{\theta_C}{\theta_C + \theta_H} \right) + \theta_H \log \left( \frac{\theta_H}{\theta_C + \theta_H} \right) \right) \\
+ \left( \frac{\theta_C + \theta_H}{\sigma_k} \right) \left( y_{0kt} + v_{kt} \left( T - \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}} c_{jnmt} \right) \right) - \frac{\theta_H}{\sigma_k} \log \left( R_{jmt} \right) \\
+ \frac{1 - \theta_C - \theta_H}{\sigma_k} \log \left( \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}} \right) - \frac{\tilde{\omega}_t}{\sigma_k} c_{jnmt} + \frac{\tilde{\gamma}_k}{\sigma_k} a_{jmt} + \frac{\tilde{\gamma}_k}{\sigma_k} \xi_{jmt} + \varepsilon_{i,jmt}
\]

I simplify the above equation by combining terms. By doing so, I arrive at the following equation, which is the one presented in the main body of the paper:

\[
V_{i,jnmt} = \delta_{kt} - \mu_k v_{kt} c_{jnmt} - \omega_{kt} c_{jnmt} - \beta_k r_{jmt} + \gamma_k a_{jmt} + \gamma_k \xi_{jmt} + \varepsilon_{i,jmt}
\]

Each coefficient is written in terms of the underlying parameters:

\[
\delta_{kt} = \frac{1}{\sigma_k} \left( \theta_C \log \left( \frac{\theta_C}{\theta_C + \theta_H} \right) + \theta_H \log \left( \frac{\theta_H}{\theta_C + \theta_H} \right) \right) \\
+ \left( \frac{\theta_C + \theta_H}{\sigma_k} \right) \left( y_{0kt} + v_{kt} \left( T - \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}} \right) \right) + \frac{1 - \theta_C - \theta_H}{\sigma_k} \log \left( \frac{1 - \theta_C - \theta_H}{(\theta_C + \theta_H) v_{kt}} \right)
\]

\[
\mu_k = \frac{\theta_C + \theta_H}{\sigma_k}
\]

\[
\beta_k = \frac{\theta_H}{\sigma_k}
\]

\[
\gamma_k = \frac{\tilde{\gamma}_k}{\sigma_k}
\]

\[
\omega_{kt} = \frac{\tilde{\omega}_k}{\sigma_k}
\]

The specification with leisure choice is empirically equivalent to the derivation without leisure choice. The optimal leisure choice is accounted for by the occupation/time fixed effects.
A.3 Derivation of location demand equation

I start from the normalized indirect utility:

\[ V_{i,j;nmt} = \delta_{kt} - \mu_k v_{kt} c_{jnmt} - \omega_{kt} e_{jnmt} - \beta_k r_{jmt} + \gamma_k a_{jmt} + \gamma_k \xi_{jmt} + \varepsilon_{i,jmt}. \]

Worker \( i \) then chooses residential neighborhood \( j \) within MSA \( m \) to maximize indirect utility. Since \( \varepsilon_{i,jmt} \) is distributed as Type I Extreme Value, the probability that worker \( i \) would choose neighborhood \( j \) is given by a multinomial logit function (McFadden (1973)). Given city \( m \) where a worker lives and works, the worker’s occupation \( k \), and the neighborhood \( n \) which the worker works in, the probability of that worker choosing to live in neighborhood \( j \) is given by

\[ s_{j|n;mt} = \frac{\exp(\hat{V}_{jnmkt})}{\sum_{j'\in J_m} \exp(\hat{V}_{j'nmkt})} \]

where \( \hat{V}_{jnmkt} = \delta_{kt} - \mu_k v_{kt} c_{jnmt} - \omega_{kt} e_{jnmt} - \beta_k r_{jmt} + \gamma_k a_{jmt} + \gamma_k \xi_{jmt} \) is the mean utility of occupation \( k \) living in \( j \) and working in \( n \).

If I observe the residential location choice conditional on work location in the data, I can back out \( \hat{V}_{jnmkt} \) directly from the data and model the mean utility directly. Unfortunately, I only observe unconditional location demand \( s_{jmkt} \). To proceed, I assume, in equilibrium, for workers in each occupation \( k \), the unconditional expected utility of working in any neighborhood \( n \) within the MSA is identical and remains identical over time. Under this simplifying assumption, I essentially take a partial equilibrium framework in which a firm’s location choice would not be affected by the change in residential sorting over the period of the analysis. I denote the expected utility value of working in each neighborhood in MSA \( m \) as \( \Lambda_{nmkt} \). The worker’s conditional residential choice probability is then given by the following equation:

\[ s_{j|nmkt} = \exp(\hat{V}_{jnmkt} - \Lambda_{nmkt}) \]

\[ \Lambda_{nmkt} = \log\left(\sum_{j'\in J_m} \exp(\hat{V}_{j'nmkt})\right), \]

which is the expected utility for workers in occupation \( k \) working in neighborhood \( n \). Under the assumption that the expected utility of working in each location is identical, I set \( \Lambda_{nmkt} = \Lambda_{mkt} \). Due to the limitation of the unconditional location choice data, this simplifying assumption is necessary.

Given the residential choice probability conditional on working in \( n \), the unconditional residential choice probability is computed by weighting these conditional probabilities with the unconditional probability of working in neighborhood \( n \) in MSA \( m \), which I denote as \( \pi_{nmkt} \). Thus, the residential choice probability is:

\[ s_{jmkt} = \sum_{n'\in J_m} \pi_{n'mkt} \cdot s_{j|n'mkt} \]

I assume the spatial distribution of jobs for each occupation- \( \pi_{n'mkt} \) as exogenous to the model within the time frame of this analysis, and the cross-sectional variation in job location is driven by
factors such as path-dependent patterns of industry clustering and firm agglomeration (Ellison and Glaeser (1997), Rosenthal and Strange (2004), Ellison, Glaeser, and Kerr (2010)). One example to illustrate this point is the concentration of financial-industry jobs in Lower Manhattan. This area has a high presence of financial jobs because financial firms are historically clustered around the southern tip of Manhattan, not because the southern tip of Manhattan is an ex-ante desirable place for financial workers to live.

After log transformation, I write the log location choice probability as a linear function of various location preference components.

$$\log \left( s_{jmk} \right) = \tilde{\delta}_{mkt} + \log \left( \sum_{n' \in J_m} \pi_{n'mkt} \exp \left( - (\omega_{kt} + \mu_{kvt}) \cdot c_{jn'mt} \right) \right)$$

$$- \beta_{kRjmt} + \gamma_{kajmt} + \gamma_{kajmt}$$

where $$\tilde{\delta}_{mkt} = \delta_{kt} - \Lambda_{mkt}$$

B Data

B.1 Residential location imputation procedure

The key dependent variable in this research is the location choice by workers of different occupations and how their location choice changes over time. The choice set for workers is the set of neighborhoods in the cities that the workers live in. The best geographic unit that captures the essence of a neighborhood would be the census tract. The boundary of a census tract is relatively stable over time, and census tracts are designed to be fairly homogeneous in terms of population and economic characteristics. Therefore, the census tract is the natural choice for the definition of neighborhood. Nevertheless, the lowest geographic identifier in the Census microdata released to the public in IPUMS is PUMA, which is a much more aggregate level than the census tract. The data that I use for occupation-specific location data at census tract level are resident count by occupation group from each census tract, provided by the NHGIS. I impute census tract level occupation-specific count of residents using census tract level summary statistics and PUMA level microdata. I document the imputation procedure below.

Since NHGIS only provide counts of residents at census tract level for aggregate occupation level $$K$$, I would only observe $$n_{jK}^j$$ for each census tract $$j$$. My goal is to impute the count of residents by detailed occupation level $$k$$, namely $$n_{j}^k$$. I do so by first imputing $$\hat{\theta}_{k|K}^j$$, which is the conditional probability of being in occupation $$k$$ given one is in occupation-group $$K$$. I compute $$\hat{\theta}_{k|K}^j$$ using IPUMS microdata at PUMA level, assuming that $$\hat{\theta}_{k|K}^j$$ is the same for every census tract $$j$$ within the same PUMA area. Then, finally compute the census tract level count of residents in occupation $$k$$, by multiplying the count of residents in occupation group $$K$$ with the imputed probability of a
worker being occupation $k$ given he/she is in occupation group $K$.

$$\hat{n}_k^j = \hat{\theta}_{k|K}^j \cdot n_k^j$$

Once I get $\hat{n}_k^j$, I generate the location choice probability for each occupation and in each city in each year $s_{jmkt}$, which is the probability of living in census tract $j$, conditional on living in MSA $m$, working in occupation $k$ and at year $t$. As I have noted in the footnote in the main manuscript, before I compute the location choice probability, I add one to each imputed $\hat{n}_k^j$ to avoid having to take log over probability zero. The share of each neighborhood among each type of workers will be used in the location choice model.

### B.2 Employment location imputation procedure

The employment location information is derived from the ZCBP from the U.S. Census Bureau, which provides establishment counts by the employment size of business establishments. The dataset comes at the level of detailed SIC and NAICS code for each zip code from 1994 on, annually. Unfortunately, the dataset does not go back farther than 1994. Therefore, I use the employment location data in 1994 to proxy those in 1990. The spatial distribution of employment changes fairly slowly over time, so I expect the four-year difference in data is unlikely to bias the data significantly.

For each zip code $z$, I first impute the employment count $n_h^z$ for each industry $h$ using establishment count and establishment sizes. Establishment size data are in the form of tabulated count: count of establishments with 1-4 employees, 5-9 employees, etc. I sum up these establishment counts weighted by the mid-value of the employee counts to impute the total employment count for each industry in each zip code. Then I use $\hat{\theta}_{k|h}$, which is the conditional probability of working in occupation $k$, given he/she works in industry $h$, to impute the number of employment in occupation $k$ at zip code $z$. $\hat{\theta}_{k|h}$ is computed using contemporaneous national microdata from IPUMS.

$$\hat{n}_k^z = \sum_h n_h^z \cdot \hat{\theta}_{k|h}$$

The set of $\hat{n}_k^z$ measured for each zip code and each occupation will form the basis of the spatial distribution of employment. I use these data and the travel time matrix to compute the expected commute time for each census tract and for workers of each occupation.

### B.3 Data acquisition procedure for travel time matrix

I acquire the travel time and travel distance from the Google Distance Matrix API (Application Programming Interface). The number of entries in the travel matrix from every census tract to every zip code within every MSA is more than 7 million (7,363,850), which is too large to extract from the API directly. One reason that such travel matrix suffers from the curse of dimensionality is that large metro areas such as New York contain a very large number of entries connecting numerous locations that are very far apart. For example, from eastern Long Island to Manhattan, there are
tens of thousands of entries connecting all zip codes to all census tracts in Manhattan and eastern Long Island, even though most of these entries have almost identical travel times and distances. Hence, it is, in fact, not necessary to compute distance and time for all entries between census tracts and zip codes. I can group various zip code destinations and compute travel distance and time from all census tracts to one destination per zip code group if the trip distance is very long, and thereby reducing the dimensionality of the data dimension.

An intuitive real-life example that demonstrates this logic would be the use of GPS navigation for a long trip. When taking a long trip by car (such as from Palo Alto to San Francisco), setting the GPS destination in whichever specific location near downtown San Francisco would not make much of a difference because one has to get on the freeway and the exact location of the destination makes relatively little impact on the ETA. However, if one takes a trip that is around 3 to 4 miles that starts and ends within San Francisco, ETA would be sensitive to the exact location of the destination.

Motivated from this observation, I only directly extract travel distance and time information between census tracts and zip code for pairs that are located within 5 miles Euclidean distance (centroids of census tracts and long/lat of zip code gazetteer). For the pairs that are farther than 5 miles apart, I proxy the location of each zip code with the closest PUMA centroid, and I extract the travel distance and time between each census tract to the assigned PUMA centroid. It significantly reduces the dimensions required for the data extract.

B.4 Historical travel time

In this section, I describe how I generate the 1990 historical travel time matrix for each MSA. Why estimate historical travel speed? If Google map existed in 1990, I could easily compute the travel time matrix using the historical traffic data. Unfortunately, the Google traffic model is only applicable to today’s traffic conditions. One obvious concern of using today’s traffic condition is a measurement error problem. But a much bigger concern is that traffic condition is a highly local variable, and it is very likely to be endogenous to location demand. Here is an example of the endogeneity problem. An exogenous demand surge (e.g., amenity shock) for a certain location X makes traffic around location X more congested, which prolongs travel time to and from location X. The long travel time into and out of location X coupled with the observation of a demand surge for location X would lead the model to interpret that the demand surge is caused by people’s desire to save on commute time. Using today’s traffic model could introduce this "self-fulfilling prophecy" that could introduce a serious endogeneity problem into the estimation of the model. Hence, the historical travel time matrix needs to be traffic information from the past.

To that purpose, I use two sources of data, Google API and the 1995 National Household Travel Survey (NHTS), to impute the historical travel time matrix. I first impute the historical travel speed (using NHTS and Google) for all travel routes within MSAs in 1995 rush hour, and then multiply the historical travel speed with travel distance (from Google) for each route to get expected travel time.
First, I use Google Distance Matrix API to obtain travel time (with traffic model turned off) and travel distance from each census tract to each zip code within each MSA. I make sure that travel time from Google is derived under the condition that the trips take place at midnight so that no traffic is expected. The traffic-free travel time gives me information on the route fixed-effects (such as the slowing-down effect of crossing a bridge, windy road, or dense city blocks with traffic lights).

Second, I use the 1995 NHTS data to fit a simple traffic speed model (Couture 2016) so that I could take the parameters estimated in the model onto the observable neighborhood characteristics in the 1990 Census and predict historical travel speed. I model travel speed as following:

$$\log(\text{speed}_{jn}) = \beta_{0,t} + \beta_{1,t} \log(\text{distance}_{jn}) + \beta_{2,t} \log(\text{distance}_{jn})^2 + \mathbf{X}_{jn} \Gamma_t + d_{jn} + \epsilon_{jnt}$$

$j$ is the origin census tract; $n$ is the destination zip code; $t$ is the year in which the trip is taken. I assume the log speed of the trip is a function of trip distance because longer trips usually have higher speeds as people take the freeway or use the main thoroughfare when the distance is long enough. I assume travel speed is also a function of the average neighborhood characteristics (population density, median income, and percentage of population working) of the origin and destination. Travel speed heavily depends on the types of neighborhoods in which the trips take place. A trip to or from densely populated neighborhoods is expected to experience heavier congestion than another trip which takes place in the suburbs. Additionally, I assume each route admits a time-invariant fixed-effects component, which accounts for the road conditions other than traffic congestion, such as a slowing-down effect of crossing a bridge, windy road, or dense city blocks with traffic lights. I assume these fixed effects do not change over time. The parameters of the model $\beta_{0,t}, \beta_{1,t}, \beta_{2,t}, \Gamma_t$ governs how location characteristics and trip distance are mapped into travel speed. Since traffic condition evolves over time, these parameters are assumed to be year-specific.

I use the 1995 NHTS data to estimate these parameters to obtain parameters applicable to 1995 traffic conditions. I restrict the trip samples to those that take place Monday to Friday and with departure time between 6:30 to 10:30 am and between 4:30 to 8:30 pm. I also restrict the trips either originate from or destine toward respondents’ location of residence. $\mathbf{X}_{jn}$ takes the location characteristics of the census tract which respondent lives in (neighborhood characteristics for the other end of the trip is unavailable). Additionally, I use Google API travel time (with traffic model turned off) to estimate the fixed-effects $d_{jn}$ for each route. I impute traffic speed using the following equation:

$$\log(\text{speed}_{jn,1995}) = \hat{\beta}_{0,1995} + \hat{\beta}_{1,1995} \log(\text{distance}_{jn}) + \hat{\beta}_{2,1995} \log(\text{distance}_{jn})^2 + \mathbf{X}_{jn} \hat{\Gamma}_{1995} + \hat{d}_{jn}.$$ 

The travel time is then obtained by multiplying imputed travel speed with travel distance:

$$\text{time}_{jn,1995} = \exp\left(\log(\text{speed}_{jn,1995})\right) \cdot \text{distance}_{jn}.$$ 

Figure A15 provides two examples of driving times on maps of Chicago and New York.
C  Descriptive statistics

C.1 Definition of central city neighborhoods

As described in the descriptive statistics section of the paper, central city neighborhoods are defined as census tracts that fall within the 5-mile pin of downtown (defined by Holian and Kahn (2015)). In Figure A1, I show the maps of a few cities as examples. In the map, the pin is defined as the point of downtown. The smaller circle represents the 3-mile radius, and the larger circle represents the 5-mile radius. The definition of central city neighborhoods in the main manuscript of the paper is given by the 5-mile radius of the downtown pin.

C.2 Neighborhood change on the map (Chicago and New York)

The first descriptive fact that I show in the paper (Figure 1) is that the income ratio between the central city and suburban neighborhoods declined precipitously and reversed dramatically after 1980. The reversal of fortune in the central cities after 1980 is the main subject of this paper. Therefore, to build intuition for such change after the 1980s, I demonstrate the neighborhood changes on maps for two prominent cities in the United States: Chicago and New York. I rank census tracts by income quintile within Chicago’s MSA and New York’s MSA, then plot the income quintile by the census tract’s distance to downtown for the four decades from 1980 to 2010. Figure A6 shows that central city neighborhoods in Chicago are overwhelmingly low-income relative to the overall MSA income level in 1980, but after several decades of increase, central city neighborhood income levels are well above the overall MSA income level. A similar pattern can be observed in New York’s central city neighborhoods in Figure A6. To various degrees, most major MSAs in the U.S. exhibit a similar pattern of income reversal between central cities and suburbs.

Furthermore, in Figure A7, I plot the census tract income quintile by distance to downtown for Chicago and New York. One can clearly see that the census tracts near downtown experienced a dramatic increase in their rank since 1980.

C.3 Central city population

The terms "gentrification" or "urban revival" may give the impression that central neighborhoods are now seeing faster overall population growth than the suburbs. However, while central neighborhoods may be gaining absolute population, they have not gained in terms of shares of overall MSA population since population growth in the suburbs continues to outpace that in central cities. Overall, American cities were still suburbanizing as recently as from 2000 to 2010, but at a much slower pace. Figure A8 shows the share of central neighborhoods’ population as a percentage of the total metropolitan population in the 25 most populous MSAs. The revived demand for central neighborhoods comes primarily from high-income workers and not all workers.
C.4 Change in work hours and commute time by wage decile

In the paper, I highlight the fact that high-wage workers experienced a rising prevalence of working long hours and a slower growth of commute time between 1980 and 2010, which coincides with the episode of gentrification. If I zoom in, I find that the sharp increase in the prevalence of working long hours occurred mainly before 2000. Coincidentally, the strong negative relationship between the growth in commute time and wage decile also mainly occurred before 2000. After 2000, both high- and low-skilled workers actually were less likely to work long hours (although low-skilled workers’ probability of working long hours decreased much more). Also, after 2000, the negative relationship between growth in commute time and wage decile disappears. In fact, the workers in the top wage decile actually experience a weakly stronger growth in commute time than workers in lower wage deciles do.

Figure A3 shows the changing probability of working long hours by wage decile for two different periods: 1. 1980 - 2000; 2. 2000 - 2010. Figure A5 shows the growth in commute time by wage decile for the same two periods. These facts are suggestive evidence that the rising value of time provided the initial force that attracted high-skilled workers into the central cities. Once the endogenous amenity process started, many high-skilled workers started to move into the city due to amenities rather than shorter commute. As amenity change evolved, the role of amenities started to overwhelm the role of shorter commute time. In fact, many high-skilled workers live in the central cities for the amenities even though they work in the suburbs. This explains why the high-wage workers experience slightly higher growth in commute time between 2000 and 2010. This evidence is also consistent with Couture and Handbury (2020)’s results in which reverse commuting became more prevalent after 2000.

Furthermore, Table A2 shows that model-predicted gentrification (by only changing the value of time) correlates much better with the sorting pattern during the 1990-2000 period than with 2000-2010, as shown by the R-squared. This is indirect evidence that the rising value of time may matter more in the first decade. Nevertheless, I do not take an explicit stance on the timing of gentrification, as my model framework is not dynamic.

D Estimation

D.1 Potential biases in estimating long-hour premium

The long-hour premium is measured off the cross-sectional relationship between weekly log earnings and weekly hours worked. One potential reason for a biased estimate for LHP (long-hour premium) is that weekly hours worked could result from workers’ labor supply choice. Therefore the variable of hours worked may be endogenous.

In the context of my estimation, the variation that I use to identify the spatial equilibrium model is the differential change in the long-hour premium. While the endogeneity of the hours variable may overstate the size of the static estimate of long-hour premium, the real threat to identification is if the change in the estimated LHP within occupations is driven by the changing degree of sorting.
on earnings and hours described above.

To fix the idea, consider the case of financial workers. Over time, it is possible that high-ability financial workers increasingly supply longer hours and receive higher earnings, relative to the low-ability counterparts. Their increasing supply of long-hour may simply due to a preference change. Meanwhile, they receive higher earnings due to their high abilities. As a result of this increasing selection by abilities, I would observe an increasing association between high earnings and high work hours among financial workers. Such association may not be driven by the increasing payoff of working long hours.

If I observe workers’ true abilities, I would re-estimate the long-hour premium controlling for the levels of ability and see whether controlling for abilities would change the estimate for LHP. The difference between LHP estimates with and without control for levels of ability indicates the degree of selection on workers’ abilities. If the degree of selection on ability increases over time, it would raise suspicion that long-hour premium estimate may be driven by increasing selection effect.

Since I do not observe workers’ unobservable abilities, I conduct a similar test on observable abilities: reported education levels. I assume that if there is increasing selection on the unobservable abilities, I should see the same increase in selection on the observable abilities, such as education levels (Altonji, Elder, and Taber (2005)).

To do that, I re-estimate the long-hour premium for several key occupations with and without controlling for education levels and compare LHP estimates.

Figure A12 shows the degree of selection on the observable skills for estimates of LHP in 1990 and 2010. The degree of selection is computed as the difference between the LHP estimates without education control and estimates with education control. Two observations can be made here: 1. there is a selection effect on the observable skill levels for almost all occupations for the level estimates of LHP in both 1990 and 2010; 2. the selection effect is larger for occupations with more skill content. These observations suggest that the level estimates of LHP are likely partly driven by the selection effect on the unobservable skill levels.

However, in Figure A13, I show the change in the degree of selection by observable skills. The selection effect, on average, is not increasing. Occupations are equally likely to see increasing and decreasing selection effects. In addition, the change in selection effect is not correlated with the skill content of occupations at all. Since the estimates for LHP is not driven by selection by the observables, the change in LHP estimated from cross-sectional data is unlikely to be driven by the changing degree of selection by the unobservables.

Table A1 in the appendix reports some of these estimates. The level estimates are smaller with education control. But the change in estimated LHP does not seem to sustain a substantial effect from adding education control.

D.2 Alternative measures of the value of time

Another variable that tracks the marginal earnings of hours supply could be constructed based on a "tournament scheme" of compensation, in which workers get paid with prizes from tournament
competitions within firms or within labor markets (Lazear and Rosen (1981)). A "prize" such as a job promotion or securing lucrative projects is awarded to the workers who outperform their competitors. Under this scheme, increasing work effort can increase the chance of winning such a prize. If the reward of a "prize" is very high, the payoff of effort is thus likely very high, since even narrowly losing the "tournament" means missing the prize entirely. Therefore, the effort level is an increasing function of the prize spread between winning and losing. Since work hour is a crucial input of worker's effort level, the marginal earnings of hours supply would rise if the reward spread between winning and losing the "tournaments" becomes higher (Bell and Freeman (2001)). A measurement of log earnings dispersion within the same occupation could track the size of the "spread" of the financial reward for workers in the occupation. Therefore, I use the Census data and compute the standard deviation of the residual log earnings for each occupation, after controlling for the individual characteristics. I use it as an alternative measurement for the value of time to check the robustness of the main results (See Table 7 Column 4).

D.3 Lasso regression using O*NET occupation characteristics

I also assess the variation in the long-hour premium by projecting the change in long-hour premium onto the 57 occupation characteristics from O*NET. I standardize the occupation characteristics by their respective mean and standard deviation so that the variation in each variable is not confounded by the scale of each characteristic. I also standardize the outcome variables (change in long-hour premium and change in earnings dispersion).

The lasso coefficients is chosen by solving the following constrained minimization problem:

$$\min_{\beta_1, \ldots, \beta_{57}} \frac{1}{N} \sum_{i=1}^{N} \left( y_i - \beta_1 x_{1i} - \cdots - \beta_{57} x_{57i} \right)^2$$

subject to $\sum_{j=1}^{57} |\beta_j| \leq t$

$y_i$ is the outcome variable, which is the change in long-hour premium. $x_{ji}$ where $j = 1, \ldots, 57$ are the 57 standardized occupation characteristics from O*NET. $t$ is some size constraint for the norm of the coefficients. There is no intercept in the regression because standardized variables are centered around zero.

One could rewrite the minimization problem with a single equation and a Lagrange multiplier $\lambda$.

$$\min_{\beta_1, \ldots, \beta_{57}} \frac{1}{N} \sum_{i=1}^{N} \left( y_i - \beta_1 x_{1i} - \cdots - \beta_{57} x_{57i} \right)^2 + \lambda \sum_{j=1}^{57} |\beta_j|$$

$\lambda$ is the weight that the regression gives to the norm of all the regression coefficients. When $\lambda$ is zero, the lasso regression coefficients are identical to those estimated from OLS regression. With a large value of $\lambda$, I penalize large values of the coefficients on any of the explanatory variable, which forces the regression coefficients to drop out and become zero if the corresponding variables do not
perform as well in predicting the variation in outcome variable and minimizing the mean squared residual. Therefore, with different levels of λ, regression coefficients would be different. A useful exercise to do would be to raise the size of λ incrementally and observe which explanatory variables drop out and which remain. Those that remain with a large size of λ tend to be those with the best explanatory power.

Finally, I use the variable selection and coefficients that give the minimum mean squared error under a 5-fold cross-validation.

Figure A14 shows the results of the Lasso analysis. Notably, "Time Pressure" is a key occupational characteristic that predicts the change in long-hour premium.

D.4 Linearization of location demand

To facilitate the estimation procedure, I linearize the location demand equation by evaluating the equation with Taylor approximation around $\omega_{zt} + \mu_z v_{kt}$ at some constant. One can think of $\omega_{zt} + \mu_z v_{kt}$ as the marginal disutility of commute time. I let $\omega_{zt} + \mu_z v_{kt} \approx \phi$, so that commute time is discounted with a constant coefficient $\phi$. Taking derivative for $\log \left( \sum_{n' \in J_m} \pi_{n'mkt} \exp \left( - (\omega_{zt} + \mu_z v_{kt}) c_{jm'n'm} \right) \right)$ with respect to $\omega_{zt} + \mu_z v_{kt}$, leads to $-\tilde{E}_t (c_{jm})$ where $\tilde{E}_t (c_{jm})$ is the expected commute on an adjusted probability measure (the adjustment depends on the size of $\phi$). Therefore, Taylor expansion around $\omega_{zt} + \mu_z v_{kt} = \phi$ equals the following equation:

$$
\log (s_{jmkt}) \approx \log \left( \sum_{n' \in J_m} \pi_{n'mkt} \exp \left( -\phi \cdot c_{jm'n'm} \right) \right) + \delta_{mkt} - \tilde{E}_t (c_{jm}) (\omega_{zt} + \mu_z v_{kt} - \phi) - \beta \gamma_{jm} + \gamma_z \log \left( \frac{N_{jm}^H}{N_{jm}^L} \right) + \theta_{kt} X_{jm} + \xi_{jmkt}
$$

The nonlinear term $\log \left( \sum_{n' \in J_m} \pi_{n'mkt} \exp \left( -\phi \cdot c_{jm'n'm} \right) \right)$ can be approximated by

$$
\log \left( \sum_{n' \in J_m} \pi_{n'mkt} \exp \left( -\phi \cdot c_{jm'n'm} \right) \right) \\
\approx \log \left( \sum_{n' \in J_m} \pi_{n'mkt,t-1} \exp \left( -\phi \cdot c_{jm'n'm} \right) \right) \\
+ \frac{\sum_{n' \in J_m} \pi_{n'mkt} \exp \left( -\phi \cdot c_{jm'n'm} \right) - \sum_{n' \in J_m} \pi_{n'mkt,t-1} \exp \left( -\phi \cdot c_{jm'n'm} \right)}{\sum_{n' \in J_m} \pi_{n'mkt,t-1} \exp \left( -\phi \cdot c_{jm'n'm} \right)} \\
= \log \left( \sum_{n' \in J_m} \pi_{n'mkt,t-1} \exp \left( -\phi \cdot c_{jm'n'm} \right) \right) + \frac{\sum_{n' \in J_m} \pi_{n'mkt} \exp \left( -\phi \cdot c_{jm'n'm} \right)}{\sum_{n' \in J_m} \pi_{n'mkt,t-1} \exp \left( -\phi \cdot c_{jm'n'm} \right)} - 1 \\
\approx \delta_{jmkt}.
$$
The term itself varies by \( j, m, k, t \). To simplify, I decompose the term into two parts. The first part is the term evaluated with the initial job location. The second part is the ratio between the expected utilities evaluated with job locations at \( t - 1 \) and job locations at \( t \), holding the distaste for commuting time constant (\( \phi \)). For feasibility reason, I assume that the ratio is constant across occupations. If jobs with a rising value of time are not becoming more concentrated in the initial locations, this assumption would not affect my estimation. Under this assumption, the first term becomes a \( j \) and \( k \) specific constant, which I write as a fixed-effects term \( \delta_{jmk} \). After some algebraic arrangement, the location demand equation can be approximated as following:

\[
\log (s_{jmk,t}) \approx \delta_{jmk} + \tilde{\delta}_{mkt} - (\phi + \omega_{zt}) \tilde{E}_{t} (c_{jmk}) - \mu_{z} v_{kt} \tilde{E}_{t} (c_{jmk}) - \beta_{z} \tau_{jmt} + \gamma_{z} \log \left( \frac{N_{jt}^{H}}{N_{jt}^{L}} \right) + \theta_{kt} X_{jm} + \xi_{jmk,t}.
\]

To provide some intuition for the expected commuting time, I construct the maps of expected commute time for some selected occupations across neighborhoods in Chicago and New York in Figure A16.

### D.5 Instrumental variables - predicted change in population

Identifying the preference parameters for amenities and rents \( \gamma \) and \( \beta \) relies on the construction of the predicted change in population for high- and low-skilled workers in each neighborhood \( j \). According to the structural model, the predicted population can be written in the following format:

\[
\hat{N}_{jmk,t} = N_{mk,t-1} \cdot \frac{\exp \left( \log (s_{jmk,t-1}) - \hat{\mu} \Delta \hat{v}_{kt} \tilde{E}_{t-1} (c_{jmk}) \right)}{\sum_{j' \in Jm} \exp \left( \log (s_{j'mk,t-1}) - \hat{\mu} \Delta \hat{v}_{kt} \tilde{E}_{t-1} (c_{j'mk}) \right)}.
\]

The equation is a function of initial location choice, expected commute time, and the change in the value of time for each occupation. Importantly, the magnitude of the predicted population change also depends on the size of \( \hat{\mu} \). While the size of \( \hat{\mu} \) is important in determining the magnitude of predicted population change, we show in this section that the size does not change the identifying variation. In other words, regardless of the size of \( \hat{\mu} \), the final estimates using the predicted changes in population as IVs should be the same.

First, I discuss the intuition of why \( \hat{\mu} \) does not matter in constructing IVs. The key identifying variation in the IVs is the variation in expected commuting time (driven by the spatial location of jobs) and the different changes in the value of time by occupation: \( \Delta \hat{v}_{kt} \tilde{E}_{t-1} (c_{jmk}) \). \( \hat{\mu} \) is simply a scaling factor.

Let us assume for now that there is only one occupation. The change in local population can thus be written as:
\[
\Delta \log \hat{N}_{jmk} = \log \left( \frac{N_{mk,t-1} \exp \left( \log \left( s_{jmk,t-1} \right) - \mu \Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{jmk} \right) \right) \right)}{\sum_{j' \in J_m} \exp \left( \log \left( s_{j'mk,t-1} \right) - \mu \Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{j'mk} \right) \right) \right)} - \log \left( N_{jmk,t-1} \right)
\]

\[
= \log N_{mk,t-1} + \log \left( s_{jmk,t-1} \right) - \mu \Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{jmk} \right) - \log \left( N_{jmk,t-1} \right)
\]

Note that the log change in the local population in occupation \( k \) is a linear function of \( \hat{\mu} \). This means that the variation in the predicted change in population is preserved regardless of the size of \( \hat{\mu} \). Even though \( \Lambda_{mkt} \) is also a function of \( \hat{\mu} \), it does not vary by neighborhood. The occupation- and city-level fixed effect will take it out.

In my estimates, however, I calculate the predicted change in population for high- and low-skilled workers, which is a sum of the number of workers across occupations. The algebra is substantially more involved. A simple linear form cannot be derived. Nevertheless, I can show that the IVs’ derivatives are largely invariant of \( \hat{\mu} \), which means that the identifying variation does not change as I vary the size of \( \hat{\mu} \).

I start by writing out the equation of the predicted change in log population of skill type \( z \):

\[
\Delta \log \hat{N}_{jmt} = \log \left( \sum_k N_{mk,t-1} \cdot \frac{\exp \left( \log \left( s_{jmk,t-1} \right) - \mu \Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{jmk} \right) \right)}{\sum_{j' \in J_m} \exp \left( \log \left( s_{j'mk,t-1} \right) - \mu \Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{j'mk} \right) \right) \right)} - \log \left( \sum_k N_{jmk,t-1} \right).
\]

I then take the derivative with respect to \( \hat{\mu} \):

\[
\frac{\partial \Delta \log \hat{N}_{jmt}}{\partial \hat{\mu}} = \frac{1}{\hat{N}_{jmt}} \left( \sum_k N_{mk,t-1} \left( -\Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{jmk} \right) s_{jmk} \sum_{j'} \Delta \hat{\nu}_{kt} \hat{E}_{t-1} \left( c_{j'mk} \right) s_{j'mk} \right) \right)
\]

Through the derivation, one can see that the marginal effect of \( \hat{\mu} \) on the change of local population is simply the interaction of the change in the value of time and the expected commute time plus a city-occupation-year level constant \( \Lambda_{kmt} \), weighted by occupation \( k \)’s share in tract \( j \), \( \hat{\rho}_{jmk} \). Since \( \hat{\mu}’ \)s impact on \( \hat{\rho}_{jmk} \) and \( \Lambda_{kmt} \) are not first-order, varying the size of \( \hat{\mu} \) simply scales the aggregate
variation in $\Delta \hat{v}_{kt}E_{t-1}(c_{jmk})$.

E Alternative decomposition exercise

Here, I present a set of exercises that try to gauge the overall impact of the changing value of time on gentrification in a framework that does not rely on or at least relies less on the model machinery presented in the paper. I run regressions at city level, exploiting cross-city variations in the changing long-hour premium, changing prevalence of long hours, and central city location choice. I implement a series of exercises in that spirit and put them in Table A9 in the appendix.

The idea of these exercises is that if amenities adjust endogenously due to the changing value of time, we may be able to gauge the size of the full effect of the changing value of time (as opposed to only the direct effect) by looking at overall levels of central city gentrification across cities and how they vary by the cities’ aggregate changing value of time.

In column 1, I present the result of regressing the actual change in central city relative log skill ratio on model-predicted change in central city relative log skill ratio across cities. In this regression, I am simple regressing the actual changes in log relative central city skill ratio on model-predicted changes (only due to the change in the value of time) in log relative central city skill ratio:

$$
\Delta \left( \ln \left( \frac{N_{H,C,mt}}{N_{L,C,mt}} \right) - \ln \left( \frac{N_{H,S,mt}}{N_{L,S,mt}} \right) \right) = a_0 + a_1 \Delta \left( \ln \left( \frac{\hat{N}_{H,C,mt}}{\hat{N}_{L,C,mt}} \right) - \ln \left( \frac{\hat{N}_{H,S,mt}}{\hat{N}_{L,S,mt}} \right) \right) + \varepsilon_m
$$

I let $m$ to index city. Result shows that $\hat{a}_1$ is far greater than one, which suggests that the observed change in the relative skill ratios in central cities most likely reflect endogenous amenity changes. Based on the coefficient $a_1$, I compute the percentage of the observed gentrification that can be attributed to the variation of the model-predicted gentrification:

$$\hat{a}_1 E \left( \Delta \left( \ln \left( \frac{\hat{N}_{H,C,mt}}{\hat{N}_{L,C,mt}} \right) - \ln \left( \frac{\hat{N}_{H,C,jt}}{\hat{N}_{L,C,jt}} \right) \right) \right)$$

$$E \left( \Delta \left( \ln \left( \frac{N_{H,C,mt}}{N_{L,C,mt}} \right) - \ln \left( \frac{N_{H,S,mt}}{N_{L,S,mt}} \right) \right) \right)$$

Column 1 result suggests that 69.84% of the observed gentrification can be attributed to the variation due to the changing value of time, suggesting that the full effect of the changing value of time is substantially larger than the direct effect, even larger than the results drawn in Table 8.

Of course, column 1 result may subject to some concerns since it is not entirely model-free. Since the model prediction contains information on city’s spatial distribution of jobs, which may correlate with other unobserved factors, $\hat{a}_1$ may be biased. I instrument the model-predicted change in relative skill ratio by the change average long-hour premium for each city (column 2), and separately by college attainment (column 3). The results are slightly smaller with the IVs compared to column 1, but still larger than half of the observed gentrification.

Next, I conduct a completely model-free exercise. I use the change in the percentage of working long hours in each city as the regressor. I use the city’s average change in LHP as the IV. In other
words, the regression can be written as:

\[
\Delta \left( \ln \left( \frac{N^H_{C,mt}}{N^L_{C,mt}} \right) - \ln \left( \frac{N^H_{S,mt}}{N^L_{S,mt}} \right) \right) = a_0 + a_1 \Delta LH_{mt} + \varepsilon_m
\]

where, \( \Delta LH_m = b_0 + b_1 \Delta v_{mt} + \omega_m \).

\( \Delta LH_{mt} \) is the change in average percentage of workers working long hours in city \( m \). \( \Delta v_{mt} \) is the change in the average LHP in city \( m \). With the estimated \( \hat{a}_1 \), I then compute:

\[
\frac{\hat{a}_1 E (\Delta LH_{mt})}{E \left( \Delta \left( \ln \left( \frac{N^H_{C,mt}}{N^L_{C,mt}} \right) - \ln \left( \frac{N^H_{S,mt}}{N^L_{S,mt}} \right) \right) \right)}.
\]

I present the result of the exercise in column 4. According to the exercise, roughly 44% of the observed variation in central city gentrification can be explained by the variation in the changing prevalence of working long hours. This again suggest that a considerably degree of gentrification can be attributed to the changing hours patterns, but the full effect is far larger than the direct effect, suggesting the endogenous amenity channel is very important.
Appendix: Figures and tables

Figure A1: Map of downtowns and the 3-mile and 5-mile ring in selected MSAs

(a) New York  (b) Chicago

(c) San Francisco  (d) Boston

Notes: The longitudes and latitudes of the downtown pins are provided by Holian and Kahn (2015). The smaller circles indicate the 3-mile (Euclidean distance) rings around the indicated downtown pins, and the larger circles indicate the 5-mile rings around the indicated downtown pins.
Figure A2: Income ratio between central city and suburban neighborhoods by MSA population ranking
Largest 10 MSAs

- **a)** 3-mile radius
- **b)** 5-mile radius
- **c)** 3-mile radius
- **d)** 5-mile radius
- **e)** 3-mile radius
- **f)** 5-mile radius
- **g)** 3-mile radius
- **h)** 5-mile radius

Notes: Central cities in these figures are census tracts that are located within 5 miles of the downtown in the respective MSAs defined in Holian and Kahn (2015). The values plotted are the mean income ratios between the central city census tracts and suburban census tracts with sample of MSAs of different population rankings.
Figure A3: Changing probability of working long hours by wage decile (>=50 hours per week)

a) 1980 - 2000
b) 2000 - 2010

Notes: Data come from IPUMS census data in 1980, 2000, 2010 (2007-2011 ACS). To compute the probability of working at least 50 hours per week, the sample I use is workers that are between 25 and 65 of age, males, and working at least 30 hours per week. I include only male in the sample to ensure that the changing female labor force participation does not distort the statistics. In a), I compute the change in probability of working long hours (>=50 hours per week) from 1980 to 2000. In b), I compute the change in probability of working long hours (>=50 hours per week) from 2000 to 2010.

Figure A4: The evolution of long-hour working

Notes: I plot the probability of working at least 50 hours a week using the CPS ASEC data from 1968 to 2016. The sample includes workers that are male, between age 25 and 65 and work at least 30 hours per week. I plot the probability of working long hours for workers in the top wage decile and the bottom wage decile over time. To smooth the plotted curve, each dot represents a three-year moving average.
Figure A5: Growth of commute time by wage decile

a) 1980 - 2000

b) 2000 - 2010

Notes: Data come from IPUMS census data in 1980, 2000, 2010 (2007-2011 ACS). I compute the change in log commute time reported in the Census/ACS data. The sample includes workers that are between 25 and 65 of age, males, working at least 30 hours per week and living in the most populous 25 MSAs in the US. In a), I plot the change in log commute time between year 2000 and 1980. In b), I plot the change in log commute time between year 2010 and 2000.
Figure A6: Income quintile by neighborhood within Chicago MSA (1980 – 2010)

(a). 1980

(b). 1990

(c). 2000

(d). 2010

Income quintile by neighborhood within New York MSA (1980 – 2010)

(e). 1980

(f). 1990
Notes: The plotted values are quintile ranking of census tract level income within the Chicago MSA and New York MSA respectively, from year 1990 to year 2010 using the Census summary statistics (NHGIS). The light color represents lowly ranked census tracts, and the darker red color represents more highly ranked census tracts in each contemporaneous year.

Figure A7: Income quintile by distance to downtown.
(a). Chicago (b). New York

Notes: The plotted values are quintile ranking of census tract level income within the Chicago MSA and New York MSA respectively. I plot the census tract income ranking from year 1980 to year 2010 against the distance (in mile) to downtown. The plot is the kernel-weighted local polynomial smoothing curve, and Epanechnikov kernel function.
Figure A8: Central city population percentage among the largest 25 MSAs.

Notes: Central cities in this graph are defined as census tracts that are located within 5 miles of the downtown pin on Google in the respective MSAs. The value plotted in the graph are the population ratio between the population in the census tracts located in the central cities and the total population in the top 25 MSAs (defined by population ranking in 1990). The source of the data is Census and ACS provided by NHGIS.

Figure A9: Work and residential location in early 1990s

Notes: Residential location data come from both IPUMS and NHGIS Census data. Details are described in the data section. The employment data come from ZCBP at zip code level. Central cities are defined as census tracts and zip codes with centroids within a 5-miles radius of the downtown pin. I use the sample from the most populous 25 MSAs to produce these graphs. The redline is the 45-degree line.
Figure A10: Residual log weekly earnings against weekly hours worked
a) Financial specialists
b) Lawyers
c) Secretaries and administrative assistants
d) Teachers

Notes: All samples come from Census data in IPUMS. ACS 2007-2011 is used for year 2010. The variables used in the plots are residual values after being regressed on individual level control variables (age, sex, race, education, industry code). The residual log earnings are normalized by constants such that the values in 1990 and 2010 start out from zero to help visual contrast. I categorize several occupations into financial specialists. Financial specialists (a) include financial managers (occ2010: 120), accountants and auditors (occ2010: 800), and securities, commodities, and financial services sales agents (occ2010: 4820). Teachers include elementary school teachers (occ2010: 2310) and secondary school teachers (occ2010: 2320). The plot is the kernel-weighted local polynomial smoothing curve, with bandwidth equals 2.5, and Epanechnikov kernel function.
Figure A11: Geographic concentration of jobs with rising long-hour premium in central cities

Notes: The figure shows the shares of jobs located in central cities based on data from the 1994 Zip Code Business Patterns. Central city neighborhoods are defined as census tracts within 5 miles of downtowns. The sample is the most populous 25 MSAs. I divide occupations into low- and high-skilled jobs. Occupations with greater than 40% of the workers having college degree are categorized as high-skilled. Within each skill category, I further categorize occupations based on the change in long-hour premium between 1990 and 2010. 37 occupations included as high-skilled and ΔLHP>=0.005; 47 occupations included as high-skilled and ΔLHP<0.005; 123 occupations included as low-skilled and ΔLHP>=0.005; 134 occupations included as low-skilled and ΔLHP<0.005. The total number of occupations is greater than those included in the model analysis, because some occupations shown in this graph cannot be merged with residential location data used for model analysis.
Figure A12: Degree of selection for long-hour premium estimates on observable skills in 1990 and 2010

a) Degree of selection in 1990

b) Degree of selection in 2010

Notes: The y-axis is the difference between the estimates of long-hour premium without controlling for education levels and the estimates controlling for education levels. The difference between the two estimates indicates the degree of selection on the observable skill levels. X-axis is the skill content of each occupation, measured as the share of college graduates in 1990 Census.

Figure A13: Change in the degree of selection for long-hour premium estimates on observable skills

Notes: The y-axis is the difference between the change in long-hour premium estimated without education control and with education control. X-axis is the skill content of each occupation, measured as the share of college graduates in 1990 Census.
Figure A14: Lasso trace plot of the O*NET characteristics at predicting change in long-hour premium

Notes: I plot the coefficients on each of the 57 O*NET occupation characteristics for different levels of lambda (regularization penalty). The outcome variable is the change in long-hour premium. The red vertical line marks the lambda selected by 10-fold cross-validation. The characteristics that are non-zero at the red line are the non-redundant characteristics.
Figure A15: Imputed 1995 rush-hour driving time

(a) Chicago (zip code: 60605)  
(b) New York (zip code: 10005)

Notes: The above maps plot travel time from each census tract to the downtown of the MSA. I designate the destination for Chicago MSA as zip code 60605 (downtown Chicago) and destination for New York MSA as zip code 10005 (downtown Manhattan). The light color represents census tract with short travel time to the center of the city and dark red color represents long travel time. The maps are shown for the purpose of demonstration. To conduct the model estimation, I impute driving time to every zip code from every census tract in the non-rural counties of the US.
Figure A16: Expected commute time for selected occupations in Chicago MSA.
(a) Financial managers  (b) Lawyers  (c) Cashiers

Expected commute time for selected occupations in New York MSA.
(d) Financial managers  (e) Lawyers  (f) Cashiers

Notes: The above maps are selected demonstrations of the expected commute time computed using employment allocation data (ZCBP data) and travel time matrix. The geographic unit displayed in the graphs is census tract. The color ranges from white to red. The light color represents short commute time, and red color represents long commute time. The color scale is consistent within respective MSA. The purpose of the maps is to show that the expected commute time by census tracts is quite different across different occupations, due to the differential distribution of job locations.
Figure A17: Changing incidence of working long hours by wage decile (1980-2010)

a) Central cities

b) Suburbs

Notes: The data come from IPUMS census data in 1980 and 2010 (2007-2011 ACS). I compute the change in the probability of working at least 50 hours per week by wage decile for workers living in central cities vs. the suburbs. The sample I use includes workers that are between 25 and 65 of age, males, and working at least 30 hours per week. I include only male in the sample to ensure that the changing female labor force participation does not distort the statistics. In a), I include only the sample of workers who live in central city neighborhoods (5 miles within downtowns). In b), I include only the sample of workers who live outside of central city neighborhoods. Wage deciles are assigned by using a national wage ranking.

Figure A18: Changing incidence of working long hours and changing commuting time by college attainment

a) Working long hours

b) Commuting time

Notes: The data come from IPUMS census data in 1980 and 2010 (2007-2011 ACS). In a), I compute the change in probability of working at least 50 hours per week by education attainment. The sample I use includes workers that are between 25 and 65 of age, males, and working at least 30 hours per week. I include only male in the sample to ensure that the changing female labor force participation does not distort the statistics. In b), I compute the change in log commute time reported in the Census/ACS data. The sample includes workers that are between 25 and 65 of age, males, working at least 30 hours per week and living in the most populous 25 MSAs in the US.
Table A1: Estimate of long-hour premium with or without controls for education

<table>
<thead>
<tr>
<th>Occupation name</th>
<th>Without educ. control</th>
<th>With educ. control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>code</td>
<td>LRP - 1990</td>
</tr>
<tr>
<td>Managers in Marketing, Advertising, and Public Relations</td>
<td>30</td>
<td>0.0173</td>
</tr>
<tr>
<td>Financial Managers</td>
<td>120</td>
<td>0.0217</td>
</tr>
<tr>
<td>Accountants and Auditors</td>
<td>800</td>
<td>0.0231</td>
</tr>
<tr>
<td>Computer Scientists and Systems Analysts/Network systems Analysts/</td>
<td>1000</td>
<td>0.0108</td>
</tr>
<tr>
<td>Web Developers</td>
<td>2100</td>
<td>0.0213</td>
</tr>
<tr>
<td>Secondary School Teachers</td>
<td>2320</td>
<td>0.0065</td>
</tr>
<tr>
<td>Securities, Commodities, and Financial Services Sales Agents</td>
<td>4820</td>
<td>0.0196</td>
</tr>
<tr>
<td>Secretaries and Administrative Assistants</td>
<td>5700</td>
<td>0.0149</td>
</tr>
</tbody>
</table>

Notes: The measurements are computed with microdata from Census IPUMS data. To compute the long-hour premium, I restrict the sample to workers between age of 25 and 65, and work at least 40 hours per week but does not work more than 60 hours per week. The results on the left are estimates without education controls, whereas the results on the right are estimates with education controls.

Table A2: Correlations between model predictions and data by decade

<table>
<thead>
<tr>
<th>Dep var: Actual change in relative log skill ratio</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted change in relative log skill ratio (only by the change in the value of time) over 1990-2010</td>
<td>11.1</td>
<td>6.559</td>
<td>4.541</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.699)</td>
<td>(0.826)</td>
<td>(1.158)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted change in relative log skill ratio (only by the change in the value of time) over 1990-2000</td>
<td>10.228</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.420)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted change in relative log skill ratio (only by the change in the value of time) over 2000-2010</td>
<td></td>
<td></td>
<td></td>
<td>5.603</td>
<td>(1.053)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(1.053)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.303</td>
<td>0.314</td>
<td>0.183</td>
<td>0.161</td>
<td>0.143</td>
</tr>
<tr>
<td>Observations</td>
<td>221</td>
<td>221</td>
<td>221</td>
<td>221</td>
<td>221</td>
</tr>
</tbody>
</table>

Notes: The table shows the coefficient of regressing the actual change in relative log skill ratio on the change in relative log skill ratio predicted by only the change in the value of time, holding all else equal. Central city is defined as census tracts within 3 miles of downtown. For column 1, the dependent variable is the actual change between year 1990 and 2010. For columns 2 and 3, the dependent variables are the actual changes during 1990-2000. For columns 4 and 5, the dependent variables are the actual changes during 2000-2010.
Table A3: Exogeneity of increasing value of time and incidence of working long hours

<table>
<thead>
<tr>
<th>Dep var</th>
<th>Δlog(long hours&lt;sub&gt;downtown&lt;/sub&gt;)</th>
<th>Δlog(long hours&lt;sub&gt;suburbs&lt;/sub&gt;)</th>
<th>Δlog(long hours&lt;sub&gt;downtown&lt;/sub&gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>ΔLHP</td>
<td>14.386</td>
<td>13.395</td>
<td>1.0402</td>
</tr>
<tr>
<td></td>
<td>(5.200)</td>
<td>(3.771)</td>
<td>(0.0822)</td>
</tr>
</tbody>
</table>

| R<sup>2</sup>    | 0.0525                              | 0.0834                            | 0.5887                              |
| Observation      | 213                                 | 214                               | 213                                 |

Notes: Each observation in the regressions represents an occupation. For column 1, the dependent variable is the change in log probability of working long hours with sample of male workers who work at least 30 hours a week and aged 25 to 65 and live in central city neighborhoods (5 miles within downtown). For column 2, the dependent variable is similarly constructed as in column 1, but with sample who live outside of central city neighborhoods. The regressor in both column 1 and 2 is the change in long-hour premium by occupation. For column 1 I regress the dependent variable in column 1 on the dependent variable in column 2.

Table A4: First-stage between actual change in skill ratio and predicted change in skill ratio

<table>
<thead>
<tr>
<th></th>
<th>Dep variable: Actual Δ log skill ratio</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td></td>
</tr>
<tr>
<td>Predicted Δ in log skill ratio</td>
<td>0.667</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0685)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted Δ change in high-skilled workers</td>
<td>-</td>
<td>2.0155</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.136)</td>
<td></td>
</tr>
<tr>
<td>Predicted Δ change in low-skilled workers</td>
<td>-</td>
<td>-0.257</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0648)</td>
<td></td>
</tr>
<tr>
<td>MSA fixed-effects</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>43,246</td>
<td>43,246</td>
<td></td>
</tr>
<tr>
<td>F-statistics</td>
<td>94.95</td>
<td>112.61</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Results shown above are OLS regressions. Each observation is a census tract. The first-difference is between 1990 and 2010. I use 2007-2011 ACS for year 2010. Column 1 reports regression result when predicted change in log skill ratio is included as the regressor. Column 1 reports regression result when change in high- and low-skilled workers are included separately as the regressors. The predicted change in log skill ratio is generated by changing only the long-hour premium in the model, assuming $\mu = 8.94$, which I obtain by estimating the location demand with only the term of commuting cost and no heterogeneity by skill. The model estimates do not respond to the value of $\mu$. Standard errors are clustered at census tract level. MSA fixed effects are used for all regressions.
Table A5: Reduced-form results from regressing the change in location demand on exogenous variables

<table>
<thead>
<tr>
<th></th>
<th>High-skilled</th>
<th>Low-skilled</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta v \times E(c)$</td>
<td>-11.963</td>
<td>-3.465</td>
</tr>
<tr>
<td></td>
<td>(0.861)</td>
<td>(0.586)</td>
</tr>
<tr>
<td>$\Delta \ln(N^H)$</td>
<td>1.894</td>
<td>-7.834</td>
</tr>
<tr>
<td></td>
<td>(0.967)</td>
<td>(0.964)</td>
</tr>
<tr>
<td>$\Delta \ln(N^L)$</td>
<td>0.996</td>
<td>8.226</td>
</tr>
<tr>
<td></td>
<td>(1.502)</td>
<td>(1.238)</td>
</tr>
<tr>
<td>$\Delta \ln(N^H) \times \text{den}$</td>
<td>5.276</td>
<td>4.126</td>
</tr>
<tr>
<td></td>
<td>(0.481)</td>
<td>(0.406)</td>
</tr>
<tr>
<td>$\Delta \ln(N^L) \times \text{den}$</td>
<td>2.882</td>
<td>0.841</td>
</tr>
<tr>
<td></td>
<td>(1.031)</td>
<td>(0.655)</td>
</tr>
<tr>
<td>$\Delta \ln(N^H + N^L) \times \text{den}$</td>
<td>-9.101</td>
<td>-5.117</td>
</tr>
<tr>
<td></td>
<td>(0.873)</td>
<td>(0.621)</td>
</tr>
<tr>
<td>$\text{den}$</td>
<td>-0.00517</td>
<td>-0.0144</td>
</tr>
<tr>
<td></td>
<td>(0.00442)</td>
<td>(0.00339)</td>
</tr>
</tbody>
</table>

Observations: 8,755,373

Notes: Results are OLS regressions, using occupation/census tract cell data from 1990 to 2010. Number of cells used is 8,755,373. This is the reduced-form result of the main model estimates. Instead of reporting the coefficients on the endogenous variable, I include the coefficients on the IVs in this regression table. The number of workers in each occupation/MSA in 1990 is used as analytical weight. I control for total expected commute (using expected commute time to jobs unrelated to workers’ occupations) and the change in expected commute time, and I allow the coefficients on total expected commute and the change in expected commute time to vary by occupation. Standard errors are clustered at census tract level.
Table A6: Gentrification decomposition – allowing for MSA population adjustments

<table>
<thead>
<tr>
<th>Dist. To downtown</th>
<th>Largest 25 MSAs</th>
<th>Largest 50 MSAs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ Value of time</td>
<td>Δ Value of time + endogenous Δ amenity + Δ rent</td>
</tr>
<tr>
<td>Actual</td>
<td>0.305</td>
<td>0.305</td>
</tr>
<tr>
<td>3 miles Model-predicted</td>
<td>0.0670</td>
<td>0.132</td>
</tr>
<tr>
<td>%</td>
<td>21.97%</td>
<td>43.28%</td>
</tr>
<tr>
<td>Actual</td>
<td>0.235</td>
<td>0.235</td>
</tr>
<tr>
<td>5 miles Model-predicted</td>
<td>0.0676</td>
<td>0.128</td>
</tr>
<tr>
<td>%</td>
<td>28.76%</td>
<td>54.47%</td>
</tr>
</tbody>
</table>

Notes: The results shown in this table show the comparison between actual changes in relative skill ratio and model-predicted changes in relative skill ratio. For the model-predicted changes, I allow the MSA’s population by skill to adjust according to the observed change. Relative skill ratio is defined as ratio between skill ratio (residents in high-skilled occupations/residents in low-skilled occupations) in central cities and skill ratio in the suburbs. I use varying definition of central city, and sample from largest 25 MSAs and largest 50 MSAs. Actual changes in relative skill ratio are computed using observed spatial data by occupation. The values shown are the mean change in skill ratio weighted by MSAs’ population.

Table A7: Gentrification decomposition – Skilled occupation = college share>30%

<table>
<thead>
<tr>
<th>Dist. To downtown</th>
<th>Largest 25 MSAs</th>
<th>Largest 50 MSAs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ Value of time</td>
<td>Δ Value of time + endogenous Δ amenity + Δ rent</td>
</tr>
<tr>
<td>Actual</td>
<td>0.332</td>
<td>0.332</td>
</tr>
<tr>
<td>3 miles Model-predicted</td>
<td>0.0142</td>
<td>0.126</td>
</tr>
<tr>
<td>%</td>
<td>4.28%</td>
<td>30.90%</td>
</tr>
<tr>
<td>Actual</td>
<td>0.252</td>
<td>0.252</td>
</tr>
<tr>
<td>5 miles Model-predicted</td>
<td>0.0125</td>
<td>0.0865</td>
</tr>
<tr>
<td>%</td>
<td>4.96%</td>
<td>34.33%</td>
</tr>
</tbody>
</table>

Notes: This table is a reproduction of Table 8 in the main manuscript. Here, I categorize occupations as high-skilled if the occupations’ initial share of college graduates in 1990 is greater than 30%. I use the parameters estimated in Table 7 column 7 for this exercise.
Table A8: Gentrification decomposition – Skilled occupation = college share > 50%

<table>
<thead>
<tr>
<th>Dist. To downtown</th>
<th>Actual</th>
<th>Model-predicted</th>
<th>Actual</th>
<th>Model-predicted</th>
<th>Actual</th>
<th>Model-predicted</th>
<th>Actual</th>
<th>Model-predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.246</td>
<td>0.0395</td>
<td>0.191</td>
<td>0.0348</td>
<td>0.191</td>
<td>0.0310</td>
<td>0.160</td>
<td>0.0348</td>
</tr>
<tr>
<td></td>
<td>0.246</td>
<td>0.140</td>
<td>0.148</td>
<td>0.134</td>
<td>0.191</td>
<td>0.120</td>
<td>0.160</td>
<td>0.107</td>
</tr>
<tr>
<td>3 miles</td>
<td>0.215</td>
<td>0.0349</td>
<td>0.123</td>
<td>0.0310</td>
<td>0.160</td>
<td>0.107</td>
<td>0.131</td>
<td>0.0348</td>
</tr>
<tr>
<td></td>
<td>0.215</td>
<td>0.131</td>
<td>0.131</td>
<td>0.119</td>
<td>0.131</td>
<td>0.119</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%</td>
<td>16.06%</td>
<td>56.91%</td>
<td>60.16%</td>
<td>60.16%</td>
<td>16.23%</td>
<td>57.21%</td>
<td>60.93%</td>
<td>60.93%</td>
</tr>
<tr>
<td>5 miles</td>
<td>0.215</td>
<td>0.131</td>
<td>0.131</td>
<td>0.119</td>
<td>0.131</td>
<td>0.119</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.215</td>
<td>0.131</td>
<td>0.131</td>
<td>0.119</td>
<td>0.131</td>
<td>0.119</td>
<td>0.131</td>
<td>0.131</td>
</tr>
<tr>
<td>%</td>
<td>18.22%</td>
<td>62.83%</td>
<td>70.16%</td>
<td>70.16%</td>
<td>19.38%</td>
<td>66.88%</td>
<td>74.38%</td>
<td>74.38%</td>
</tr>
</tbody>
</table>

Notes: This table is a reproduction of Table 8 in the main manuscript. Here, I categorize occupations as high-skilled if the occupations’ initial share of college graduates in 1990 is greater than 50%. I use the parameters estimated in Table 7 column 8 for this exercise.

Table A9: MSA-level gentrification regressions

<table>
<thead>
<tr>
<th>Dep var: Observed change in relative log skill ratio over 1990-2010</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted change in relative log skill ratio (only by the change in the value of time) over 1990-2010</td>
<td>11.100</td>
<td>10.297</td>
<td>8.484</td>
<td>9.020</td>
</tr>
<tr>
<td>Δ pct in long hours (1990-2010)</td>
<td>(1.137)</td>
<td>(2.873)</td>
<td>(2.912)</td>
<td>(1.676)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>OLS or IV</th>
<th>OLS</th>
<th>IV</th>
<th>IV</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>IV</td>
<td>N/A</td>
<td>Δ pct in long hours</td>
<td>Δ pct in long hours by skill</td>
<td>Δ mean LHP</td>
</tr>
<tr>
<td>Observations</td>
<td>221</td>
<td>221</td>
<td>221</td>
<td>221</td>
</tr>
<tr>
<td>% of observed change predicted by the independent variable</td>
<td>69.84%</td>
<td>64.79%</td>
<td>53.38%</td>
<td>43.53%</td>
</tr>
</tbody>
</table>

Notes: Column 1 shows the coefficient of regressing the actual change in relative log skill ratio on the change in relative log skill ratio predicted by only the change in the value of time, holding all else equal. For columns 2 and 3, I instrument the independent variable with the change in the average percentage of working long hours by city (MSA). In column 4, I use the change in the average percentage of working long hours as independent variable, and I instrument it with the change in mean long-hour premium.
Table A10: The Long-hour premium and its change by occupation

<table>
<thead>
<tr>
<th>Occupation</th>
<th>LHP 1990</th>
<th>LHP 2010</th>
<th>ΔLHP 1990-2010</th>
<th>High-skill indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Managers in Marketing, Advertising, and Public Relations</td>
<td>0.0161</td>
<td>0.0214</td>
<td>0.0053</td>
<td>1</td>
</tr>
<tr>
<td>Financial Managers</td>
<td>0.0180</td>
<td>0.0246</td>
<td>0.0066</td>
<td>1</td>
</tr>
<tr>
<td>Human Resources Managers</td>
<td>0.0145</td>
<td>0.0185</td>
<td>0.0039</td>
<td>1</td>
</tr>
<tr>
<td>Purchasing Managers</td>
<td>0.0149</td>
<td>0.0182</td>
<td>0.0033</td>
<td>1</td>
</tr>
<tr>
<td>Education Administrators</td>
<td>0.0134</td>
<td>0.0125</td>
<td>-0.0009</td>
<td>1</td>
</tr>
<tr>
<td>Medical and Health Services Managers</td>
<td>0.0181</td>
<td>0.0181</td>
<td>0.0001</td>
<td>1</td>
</tr>
<tr>
<td>Managers, nec (including Postmasters)</td>
<td>0.0157</td>
<td>0.0154</td>
<td>-0.0003</td>
<td>1</td>
</tr>
<tr>
<td>Compliance Officers, Except Agriculture</td>
<td>0.0141</td>
<td>0.0209</td>
<td>0.0068</td>
<td>1</td>
</tr>
<tr>
<td>Human Resources, Training, and Labor Relations Specialists</td>
<td>0.0167</td>
<td>0.0235</td>
<td>0.0068</td>
<td>1</td>
</tr>
<tr>
<td>Management Analysts</td>
<td>0.0169</td>
<td>0.0168</td>
<td>-0.0002</td>
<td>1</td>
</tr>
<tr>
<td>Accountants and Auditors</td>
<td>0.0198</td>
<td>0.0259</td>
<td>0.0062</td>
<td>1</td>
</tr>
<tr>
<td>Insurance Underwriters</td>
<td>0.0192</td>
<td>0.0286</td>
<td>0.0094</td>
<td>1</td>
</tr>
<tr>
<td>Computer Scientists and Systems Analysts/Network systems</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analysts/Web Developers</td>
<td>0.0102</td>
<td>0.0145</td>
<td>0.0043</td>
<td>1</td>
</tr>
<tr>
<td>Computer Programmers</td>
<td>0.0091</td>
<td>0.0131</td>
<td>0.0041</td>
<td>1</td>
</tr>
<tr>
<td>Operations Research Analysts</td>
<td>0.0108</td>
<td>0.0127</td>
<td>0.0019</td>
<td>1</td>
</tr>
<tr>
<td>Architects, Except Naval</td>
<td>0.0130</td>
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Registered Nurses  0.0165  0.0137 -0.0028  1
Physical Therapists  0.0243  0.0126 -0.0117  1
Speech Language Pathologists  0.0106  0.0057 -0.0049  1
Therapists, nec  0.0158  0.0080 -0.0078  1
Clinical Laboratory Technologists and Technicians  0.0144  0.0099 -0.0045  1
Advertising Sales Agents  0.0174  0.0230  0.0055  1
Insurance Sales Agents  0.0137  0.0186  0.0049  1
Securities, Commodities, and Financial Services Sales Agents  0.0157  0.0355  0.0197  1
Airline Pilots and Flight Engineers  0.0059  0.0037 -0.0023  1
Farmers, Ranchers, and Other Agricultural Managers  0.0087  0.0085 -0.0002  0
Food Service and Lodging Managers  0.0172  0.0126 -0.0047  0
Property, Real Estate, and Community Association Managers  0.0174  0.0144 -0.0029  0
Wholesale and Retail Buyers, Except Farm Products  0.0212  0.0199 -0.0013  0
Purchasing Agents, Except Wholesale, Retail, and Farm Products  0.0149  0.0172  0.0022  0
Claims Adjusters, Appraisers, Examiners, and Investigators  0.0133  0.0111 -0.0022  0
Other Business Operations and Management Specialists  0.0147  0.0235  0.0088  0
Drafters  0.0213  0.0148 -0.0065  0
Engineering Technicians, Except Drafters  0.0167  0.0129 -0.0038  0
Surveying and Mapping Technicians  0.0129  0.0147  0.0018  0
Chemical Technicians  0.0170  0.0206  0.0035  0
Life, Physical, and Social Science Technicians, nec  0.0125  0.0113 -0.0012  0
Paralegals and Legal Assistants  0.0221  0.0169 -0.0051  0
Preschool and Kindergarten Teachers  0.0104  0.0091 -0.0013  0
Teacher Assistants  0.0054  0.0143  0.0089  0
Designers  0.0179  0.0134 -0.0044  0
Photographers  0.0164  0.0069 -0.0096  0
Respiratory Therapists  0.0126  0.0132  0.0006  0
Dental Hygienists  0.0231  0.0006 -0.0225  0
Health Diagnosing and Treating Practitioner Support Technicians  0.0137  0.0165  0.0028  0
Licensed Practical and Licensed Vocational Nurses  0.0186  0.0122 -0.0064  0
Health Technologists and Technicians, nec  0.0180  0.0228  0.0048  0
Dental Assistants  0.0106  0.0079 -0.0028  0
Medical Assistants and Other Healthcare Support Occupations, nec  0.0124  0.0171  0.0047  0
First-Line Supervisors of Police and Detectives  0.0035  0.0066  0.0031  0
Firefighters  0.0044  0.0086  0.0042  0
Sheriffs, Bailiffs, Correctional Officers, and Jailers  0.0105  0.0095 -0.0010  0
Police Officers and Detectives  0.0117  0.0122  0.0005  0
Security Guards and Gaming Surveillance Officers  0.0177  0.0174 -0.0003  0
Crossing Guards  0.0349  0.0111 -0.0238  0
Law enforcement workers, nec  0.0143  0.0155  0.0013  0
Chefs and Cooks  0.0188  0.0174 -0.0014  0
First-Line Supervisors of Food Preparation and Serving Workers  0.0219  0.0211 -0.0008  0
Food Preparation Workers  0.0157  0.0112 -0.0045  0
Bartenders  0.0119  0.0065 -0.0054  0
Counter Attendant, Cafeteria, Food Concession, and Coffee Shop  0.0115  0.0050 -0.0064  0
Waiters and Waitresses  0.0104  0.0069 -0.0034  0
Food preparation and serving related workers, nec  0.0113  0.0082 -0.0031  0
First-Line Supervisors of Housekeeping and Janitorial Workers  0.0137  0.0164  0.0027  0
First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers  0.0190  0.0134 -0.0056  0
Janitors and Building Cleaners  0.0150  0.0120 -0.0029  0
Maids and Housekeeping Cleaners  0.0050  0.0060  0.0009  0
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Carpenters | 0.0110 | 0.0073 | -0.0037 | 0
Carpet, Floor, and Tile Installers and Finishers | 0.0179 | 0.0132 | -0.0047 | 0
Cement Masons, Concrete Finishers, and Terrazzo Workers | 0.0035 | 0.0128 | 0.0093 | 0
Construction Laborers | 0.0183 | 0.0126 | -0.0057 | 0
Construction equipment operators except paving, surfacing, and tamping equipment operators | 0.0126 | 0.0083 | -0.0042 | 0
Drywall Installers, Ceiling Tile Installers, and Tapers | 0.0094 | 0.0069 | -0.0025 | 0
Electricians | 0.0131 | 0.0106 | -0.0025 | 0
Painters, Construction and Maintenance | 0.0164 | 0.0102 | -0.0061 | 0
Pipayers, Plumbers, Pipefitters, and Steamfitters | 0.0073 | 0.0114 | 0.0040 | 0
Roofers | 0.0150 | 0.0091 | -0.0059 | 0
Sheet Metal Workers, metal-working | 0.0136 | 0.0124 | -0.0011 | 0
Structural Iron and Steel Workers | 0.0076 | 0.0108 | 0.0032 | 0
Helpers, Construction Trades | 0.0124 | 0.0113 | -0.0011 | 0
Construction and Building Inspectors | 0.0092 | 0.0044 | -0.0048 | 0
First-Line Supervisors of Mechanics, Installers, and Repairers | 0.0109 | 0.0122 | 0.0013 | 0
Computer, Automated Teller, and Office Machine Repairers | 0.0100 | 0.0138 | 0.0038 | 0
Radio and Telecommunications Equipment Installers and Repairers | 0.0153 | 0.0100 | -0.0053 | 0
Aircraft Mechanics and Service Technicians | 0.0118 | 0.0093 | -0.0025 | 0
Automotive Body and Related Repairers | 0.0101 | 0.0121 | 0.0020 | 0
Automotive Service Technicians and Mechanics | 0.0129 | 0.0110 | -0.0019 | 0
Bus and Automotive Mechanics and Diesel Engine Specialists | 0.0128 | 0.0125 | -0.0003 | 0
Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics | 0.0145 | 0.0125 | -0.0020 | 0
Heating, Air Conditioning, and Refrigeration Mechanics and Installers | 0.0115 | 0.0096 | -0.0018 | 0
Industrial and Refractory Machinery Mechanics | 0.0185 | 0.0169 | -0.0016 | 0
Maintenance and Repair Workers, General | 0.0130 | 0.0150 | 0.0020 | 0
First-Line Supervisors of Production and Operating Workers | 0.0145 | 0.0151 | 0.0006 | 0
Electrical, Electronics, and Electromechanical Assemblers | 0.0192 | 0.0197 | 0.0005 | 0
Assemblers and Fabricators, nec | 0.0172 | 0.0178 | 0.0006 | 0
Bakers | 0.0110 | 0.0158 | 0.0048 | 0
Butchers and Other Meat, Poultry, and Fish Processing Workers | 0.0097 | 0.0166 | 0.0069 | 0
Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic | 0.0176 | 0.0212 | 0.0036 | 0
Machinists | 0.0188 | 0.0208 | 0.0020 | 0
Tool and Die Makers | 0.0201 | 0.0197 | -0.0005 | 0
Welding, Soldering, and Brazing Workers | 0.0154 | 0.0176 | 0.0022 | 0
Metal workers and plastic workers, nec | 0.0194 | 0.0216 | 0.0022 | 0
Bookbinders, Printing Machine Operators, and Job Printers | 0.0196 | 0.0161 | -0.0035 | 0
Laundry and Dry-Cleaning Workers | 0.0167 | 0.0092 | -0.0075 | 0
Sewing Machine Operators | 0.0139 | 0.0060 | -0.0078 | 0
Tailors, Dressmakers, and Sewers | 0.0078 | 0.0090 | 0.0012 | 0
Cabinetmakers and Bench Carpenters | 0.0127 | 0.0165 | 0.0038 | 0
Stationary Engineers and Boiler Operators | 0.0108 | 0.0127 | 0.0018 | 0
Crushing, Grinding, Polishing, Mixing, and Blending Workers | 0.0221 | 0.0215 | -0.0006 | 0
Cutting Workers | 0.0183 | 0.0260 | 0.0077 | 0
Inspectors, Testers, Sorters, Samplers, and Weighers | 0.0135 | 0.0193 | 0.0059 | 0
Medical, Dental, and Ophthalmic Laboratory Technicians | 0.0218 | 0.0213 | -0.0006 | 0
Packaging and Filling Machine Operators and Tenders | 0.0133 | 0.0151 | 0.0018 | 0
Painting Workers and Dyers | 0.0147 | 0.0197 | 0.0050 | 0
Photographic Process Workers and Processing Machine Operators | 0.0189 | 0.0151 | -0.0038 | 0
Other production workers including semiconductor processors and cooling and freezing equipment operators | 0.0188 | 0.0182 | -0.0005 | 0
<table>
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<tr>
<th>Occupation</th>
<th>Rate 1</th>
<th>Rate 2</th>
<th>Rate 3</th>
<th>Rate 4</th>
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<tr>
<td>Supervisors of Transportation and Material Moving Workers</td>
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<td>0.0151</td>
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<td>Flight Attendants and Transportation Workers and Attendants</td>
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<td>0.0118</td>
<td>0.0064</td>
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<tr>
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<tr>
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<td>Laborers and Freight, Stock, and Material Movers, Hand</td>
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<tr>
<td>Packers and Packagers, Hand</td>
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